# Audience - Performer Engagement in Live Dance

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# Abstract

In live performances seated audiences have restricted opportunities for response, most commonly through cheering and applause at the end. However, audiences make other apparently incidental movements during a performance such as fixing hair, adjusting glasses, scratching ears, supporting their chin or shifting their bodies in the chair to change posture. The question we address here is whether these apparently incidental movements may provide systematic clues about people's level of engagement with a performance. Our programmatic hypothesis is that audiences' ongoing responses are part of a bi-directional system of audience-performer communication that distinguishes live from recorded performance. What could performers be detecting in these situations that informs their dynamic sense of how well a performance is going? Existing audience research has mostly focused on the non-visible or self-reported responses, while little is known about the overt audience responses. The main aim of this research is to uncover these audience responses and examine whether they may provide an indication of audience engagement and thereby form part of a feedback cycle between the performers and their audience. This thesis investigates this in the hardest case of contemporary dance where the production and setting should make audience responses hard to detect. A series of live performance studies is conducted in real theatrical settings in UK. This requires the development of methods capable of capturing continuous responses of the audience and the dancers and making sense of the resulting multi-modal data. Video recordings of performers and audience are analysed using computer vision techniques to extract face and body movement data while audience hand movement is captured using specialised wearable devices. The results show that while there is no systematic relationship between the responses of audience and dancers, audience members body movements do signal their levels of engagement to the dancers. The empirical findings of this thesis provide evidence that stillness and blank expressions are characteristic markers of cognitive engagement during performance whereas movement and hand to face gestures typically signal restlessness or boredom. This work argues that the audience's overt responses matter and are an important characteristic of the live experience. The audience responses that have been disclosed in this thesis can provide a systematic basis to design for audiences and suggest new forms of live experience more focused on the audience.

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# Statement of Originality

I, Lida Theodorou, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below. I attest that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge break any UK law, infringe any third party's copyright or other Intellectual Property Right, or contain any confidential material. I accept that the College has the right to use plagiarism detection software to check the electronic version of the thesis. I confirm that this thesis has not been previously submitted for the award of a degree by this or any other university. The copyright of this thesis rests with the author and no quotation from it or information derived from it may be published without the prior written consent of the author.

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# List of abbreviations

| | |
|---|---|
| ACC | Acceleration |
| AHM | Audience Hand Movement |
| AHTM | Audience Head and Torso Movement |
| AM | Audience Movement |
| AP | Audio Power |
| BLE | Bluetooth Low Energy |
| DM | Dancers Movement |
| fMRI | Functional Magnetic Resonance Imaging |
| fps | Frames per second |
| GLMM | Generalised Linear Mixed Model |
| GLM | Generalised Linear Model |
| GSR | Galvanic Skin Response |
| HCI | Human-Computer Interaction |
| IR | Infrared |
| MoCap | Motion Capture |
| LCD | London Contemporary Dance School |
| LRT | Likelihood Ratio Test |
| MAD | Mean Absolute Deviation |
| pARF | Portable Audience Response Facility |
| PPG | Photoplethysmography Sensor |
| PM | Projection Movement |
| RMS | Root Mean Square |
| STG | Self-Touching Gestures |
| TS | Time Series |
| TMS | Transcranial Magnetic Stimulation |

# Chapter 1

# Introduction

> "When you reach the eventual audience, the great barometer is silence. If you listen carefully you can learn everything about a performance from the degree of silence it creates. Sometimes an emotion ripples through the audience and the quality of the silence is transformed. A few seconds later and you can be in a different silence, and so on, passing from a moment of great intensity to a moment less intense, when the silence will inevitably weaken. Someone will cough, or fidget, and as boredom settles in, it will express itself through a person shifting his weight, so that the springs of his seat creak and the hinges squeak, or, worst of all, you hear a hand opening a programme (Brook, 2017)"

There is something special about attending a live performance, being in a crowded auditorium in the dark watching your favourite actor, dancer or singer. According to Encore Tickets (Devlin et al., 2017), 59% of people say they have felt emotionally affected by a live performance, and 46% say they enjoy a theatre experience because of the atmosphere that comes with being part of an audience. Research by O'Neil et al. (2014) which looked at the cultural value of London opera audiences, suggested that opera attendance is a social activity and not a private one. Even those opera enthusiasts who went on their own and who had quite individual aesthetic responses to opera were very aware of the audience around them, and this co-presence was highly significant to their appreciation for the performance, even if they had no apparent interaction with other members of the audience (O'Neil et al., 2014).

Having an audience is also very important for the performers on stage. It has been shown that performers tend to become more expressive when performing in front of an audience compared to when they are rehearsing (Moelants et al., 2012). Performers can potentially draw from the appreciative energy of the audience making them not only feel better about their work but also actually leading them to physically perform at a higher level. The impact of this interaction can be substantial from the side of the performer (Pines and Giles, 2017), even if the audience is not always aware of it.

This co-presence of audience and performers is an important element of live performances that distinguishes them from recorded ones. Despite its importance, there is very little research on the effects of this co-presence, i.e. how an audience perceives and responds to a live performance as well as the way performers detect and respond to audience reactions (although see Katevas et al., 2015; Gardair et al., 2011; Vincs et al., 2010; Healey et al., 2009; Harris, 2017 and others).

The nature of a live audience has changed substantially throughout history. In early instances such as at the Comedie-Francais and the Greek theatre the behaviour of audiences was loud and disruptive and responses were not just obvious but they entirely dominated the performances (Dietz, 2017). Today's traditional performances on the other hand seem to dictate more strictly the behaviour of the audience members by having them sit behind an imaginary line in the dark, silently observing the performers. This behaviour is dictated more strongly in specific types of performances such as opera, theatre or dance and less in cases such as stand-up comedy or concerts where the ongoing feedback between audience and performers can be especially obvious e.g. through the use of shouting, laughter and heckles.

The newly-introduced strict separation of the two groups (audience and performers) makes the reactions of today's traditional audiences harder to comprehend by the performers. Being the most visible and audible group of this interaction, the performers are limited in what they can see or hear of an audience which is, in turn, given very limited opportunities to respond. The primary conventional method for the members of this audience to express their satisfaction or dissatisfaction within a performance is through applause and/or cheering. Nonetheless, audiences have notoriously recruited other means of response to the performance including the organised and carefully timed use of apparently innocent activities such as coughing or fidgeting (Broth, 2011; Wagener, 2012). These kind of responses might not consciously directed to the performers or to the rest of the audience but they might be good indicators of audience engagement or boredom.

This clear separation also makes the behaviour of the audience very difficult to manipulate. While it is unlikely that performance practitioners have specific emotional targets in mind, they would presumably not want the audience to feel bored, droopy or sleepy during a performance. In the past, as much as today, directors and choreographers have certain expectations from an audience during a performance and they frequently use different techniques to influence audience responses. An interesting example from the classical times was the employment of "claquers", organised bodies of professional applauders. These professionals were employed in French theatre and opera houses to influence the audience to applaud during specific parts of the performance (Barry, 2013) though the idea mostly died out in Europe and America during the 20$^{\text{th}}$ century.

The programmatic hypothesis of this thesis is that audience responses are part of a system of real-time audience-to-audience and audience-to-performer feedback loop that distinguishes live from recorded performance. A key motivation to explore this hypothesis is that performers routinely distinguish between "good" or "bad" audiences and between specific moments of engagement or "lift" and moments of boredom in an audience (Healey et al., 2009). Even though these are arguably the moments that characterise a live performance, little is known about how, why or when they occur.

This thesis considers the challenging case of contemporary dance. In a typical dance performance the audience will be in the dark and the performers behind bright lights with loud music drowning out other sounds. This places severe limitations on what dancers are able to sense, even in principle, what the audience responses are during a performance. In addition they also need to contend with the physical and cognitive demands of the dance performance itself. A further limitation on the potential for concurrent feedback between audiences and performers is introduced by the conventions about what forms of audience response are considered appropriate; laughter is rare and concurrent shouting and heckling are definitely frowned upon.

This raises the question: what are the overt audience responses that contribute to the experience of a live performance? Can these responses provide signs of how engaged or bored the audience is during the performance? This thesis aims to uncover these responses by exploring some of the ways an individual may respond to contemporary dance. In particular, this research will focus on the role of gesture, body movement and facial expressions of audience members while watching contemporary dance performances.

## 1.1 Methodological approach

To achieve a detailed investigation of audience reactions during a performance, the methodology of this thesis follows a concurrent and post performance approach developed to take into account both the research goals mentioned above, but also the practical demands of data collection in live theatrical settings. Given that performances unfold in time, and that audience engagement is very difficult to capture after the act, the methods adopted combine qualitative and quantitative data with a focus on continuous metrics.

The study of audiences in live performance requires elements borrowed from multiple fields. Non-verbal interaction theories and engagement definitions from human computer interaction (HCI) are useful tools to understand audience momentary responses (More information on this in section 2.5 in Chapter 2). In contrast to several methods that other researchers used in the past (presented in Chapter 3), our methodology benefits from the fact that the primary method of audience data collection is supported by continuous data collected during and not after a performance. This method was combined with the use of post-performance questionnaires which were used as a secondary data collection method mostly to support the findings that came out from the continuous datasets. By combining the literature, approaches and methods of these different perspectives, this methodological intervention gives the most accurate understanding of these interactional fine grained dynamics that occur during a live performance.

In particular, this research consisted of three large-scale empirical studies that took place in theatres in the UK. During these studies we collected continuous and post performance audience data during six dance performances. For a continuous data collection methodology that can be applied in a real theatre, we firstly followed a video-based approach combined with methods from the area of computer vision (Study I, Chapter 4, Study II, Chapter 5) followed by the use of wearable devices (Study III, Chapter 6). To test specific hypotheses, in studies II and III (Chapters 5,6) continuous measurements were combined with post performance surveys. For Study II and Study III the evaluation approach was adapted, based on the experience gained from Study I, and the demands of the particular study context. These amendments are introduced in the respective study chapters (Chapter 5, Chapter 6).

The rationale and decision-making process behind this mixed-method approach and a detailed description of the methods used are presented in Chapter 3.

## 1.2 Contributions

This thesis is an attempt to partially answer the questions discussed above by exploring some of the ways an audience may respond to contemporary dance. Understanding audiences and designing for them is a multidisciplinary concern, significant not only in the field of audience research, which we argue here to be an emerging discipline in its own right, but also to a range of other disciplines such as psychology and social sciences, performance studies, HCI and affective computing. Thus, this thesis makes the following contributions as described below:

**1.** It is a first attempt to uncover dynamic processes underpinning audience engagement that are based on the overt audience activities and on the bi-directional audience-performer and audience-audience relationship discussed above. This can potentially contribute to the work of art practitioners, enhance audience experience as well as improve the work of other audience researchers. It is supported with empirical evidence from the three studies of live performances presented in Chapters 4, 5 and 6. A detailed discussion on this is presented in Chapter 7.

**2.** Within the framework of performance studies, this thesis has practical value for performance practitioners in identifying and evaluating techniques and strategies that have both artistic and financial significance. Understanding and sensing the audience can act as an evaluation tool to help performance directors understand how a performance is received and how their audience feels and reacts while the performance unfolds. Artistically, the results of this thesis can inform the creative production process of performance practitioners. Financially, since arts organisations and scholars of the audience experience of art are increasingly concerned with the ways in which audience members make sense of their experiences of the arts, the methods and findings of this thesis can be used to provide feedback to arts organisations.

**3.** This thesis suggests a new methodological approach to measure audience responses during a performance that can inform and be adopted by other audience researchers. In particular, the thesis proposes new ways to measure continuous audience engagement in real-theatrical settings. It focuses on the collection of explicit audience data using cameras and wearable devices and without tethering the audiences with any hand-held devices (Chapter 4-6). It proposes a novel approach of tightly integrating concurrent and post performance methods for measuring engagement of live audiences (Chapters 5,6). Finally, it suggests a low-cost method for automatic hand tracking in an audience using reflective wristbands and computer vision techniques (Chapter 5). The techniques discussed in this thesis can be applied partially or in their totality to other situations such as for audiences in teaching or advertising.

## 1.3 Outline of this Document

This thesis is structured around eight chapters.

**Chapter 2** starts by presenting reviews from performance and cultural studies that have focused on audience interactions and presents examples of participating, seated and dance audiences. The last section of the chapter presents the existing literature on non-verbal cues of engagement and boredom and explains how these can be applied in the case of live audiences. The chapter concludes that there is very little research on overt audience responses and the interpretation of audience physical responses during a live performance.

**Chapter 3** sets out the methodological approach of this research. It firstly explains the data collection approach we follow in this research. It then gives an overview of existing methods that have been used to measure audience responses and explains how most of them are not appropriate to answer the questions of interest in this research. Chapter 3 concludes by giving a brief overview of the methods used in this research.

**Chapters 4,5,6** present and discuss the three empirical studies conducted in this research. As discussed above in order to answer the research questions of this thesis, the studies were carried out in the following real theatre settings: 1. The Theatre Royal in Glasgow (Chapter 4) 2. The Place theatre in London (Chapter 5) 3. Sadler's Wells theatre in London (Chapter 6).

**Chapter 7** draws together the findings of the three studies and provides a structured overview that discusses social and cultural aspects. It also relates the findings to previous research and discusses and evaluates the methodological approach used in this thesis.

**Chapter 8** summarises the findings of the three studies, recapitulates the contributions, refers to limitations, and concludes the thesis with potential avenues for future works.

## 1.4 Associated Publications

- Theodorou, L., Healey, P.G.T., and Smeraldi, F., (2019), Engaging with Contemporary Dance: What Can Body Movements Tell us About Audience Responses? Frontiers in Psychology 10. https://doi.org/10.3389/fpsyg.2019.00071

- Theodorou, L. and Healey, P. G.T. (2017) What can hand movements tell us about audience engagement? In Proceedings of the 39th Annual Conference of the Cognitive Science Society.

- Theodorou, L., Healey, P.G.T., and Smeraldi, F. (2016) “Exploring Audience Behaviour During Contemporary Dance Performances" *Proceedings of the 3rd International Symposium on Movement and Computing - MOCO ’16.*

# Chapter 2

# Related work

## 2.1 Overview

This chapter sets out the research topic of the thesis. It provides a thorough and multidisciplinary review of concepts, which will be used as a baseline for the discussion and interpretation of the results in the following chapters. It begins with a historical review from the fields of cultural and performance studies, in order to show that the question of audience activity during a performance has generally been ignored. It then focuses on audience-performer interactions and the importance of the live experience. Finally, section 2.5 puts forward some general definitions of audience engagement and presents existing research on audience engagement and non-verbal behaviour.

## 2.2 Audiences in different contexts

In its simplest definition an audience is a group of people that experience an event. Depending on the type of the event, and the general context around it, the audience can take many forms. It can be thought of as the listeners or spectators of radio or TV programmes, readers of books, columns and articles as well as spectators of live sports, theatre or opera (Livingstone, 2003). The definition is so broad it does not determine physical co-location of the audience to the event, the event being live or even it being visual or aural.

This thesis is interested only in a subset of these possible contexts: audience members in live contemporary dance. This is a narrow definition and it will become apparent from the literature that follows. Little attention has been paid to understanding how that kind of audience behaves, what its relationship is to the dancers and to the performance, and how individual audience members affect the rest of the group. Given the narrowness of the topic and the lack of research, this thesis extends and covers related contexts where there is relevant research or where audiences have been studied more extensively. The two following sections describe examples from related contexts: ones that are more participatory such as audiences during historical theatre or today's immersive theatre and seated audiences that are more common in today's modern traditional theatre. This section finishes by presenting some existing research specifically on dance audiences.

### 2.2.1 Participating audience

In contrast to traditional theatre where audiences are urged to sit quietly in a dark auditorium during a performance, there were cases in the past and fewer today where the separation between an actor and the spectator was bridged. For centuries theatre audiences were undisciplined; they used their right, as an audience, to tyrannise the actors, to challenge the dramatist's text, and to talk to the other audience members (Pasquier, 2015). From the time that permanent public theatres were first built in London in the late sixteenth century on to the early nineteenth century, governments considered English theatre and theatre audiences to be problems of law and order (Butsch, 2010). Theatres did not have fixed seats and the audience was expected to stand and was able to move around. Performances were scheduled during daylight, so that audience members were visibly reminded that they were part of a crowd. The audience was not obliged to pay and could leave at any time. For this reason the performers had to attract and retain audiences. They did so by directly addressing audiences, engaging them by incorporating them into the script, and even descending from the stage to mingle with them. Performers were undoubtedly at the mercy of their audiences.

Apart from the disruptive audience behaviour described above there were also some cases where the performance was designed specifically to enhance audience participation. In the "Theatre of the Oppressed" by the Brazilian director Augusto Boal (Boal, 1979), the participants were invited to act out a variety of different endings. The latter was a type of a forum theatre in which audience members were urged to intervene by stopping the action, coming on stage to replace the actors and become a "spect-actor". They were allowed to propose a different solution to the play and act using their own ideas and thoughts. When the act was completed a discussion took place among the audience, with the director playing the role of the moderator. Similar to Boal, Richard Schechner (Schechner, 1994) was one of the two inventors of performance studies as a discipline. Schechner started thinking about new ways of performance and introduced a new set of empirical methods, including ethnography. An important example of Schechner's experimentation with performance was "The New Orleans Group" which explored the practices of environmental theatre.

Environmental theatre was an early form of what we call today site-specific theatre where audiences are active members of the setting. The audience of the environmental theatre was invited and even expected, to participate. Through this kind of theatre, Schechner investigated how the performers experienced space as well as the impact that the participation of the audience has on the performance. As opposed to traditional western theatre, in environmental theatre performers and audience members need to have equal access to the space where the performance takes place.

In a similar vein, two British companies named Punchdrunk and Shunt produced a different kind of site-specific theatre that endorsed audience participation. Both companies produced different kinds of immersive theatre in which the audience was free to choose what to watch and decide where to go. Immersive theatre refers to any performance that puts the audience into the scene and sometimes gives bodily involvement in the action (White, 2012). All the examples above are cases where the audience is invited to take an explicit role in participating and shaping what happens in the piece.

Today, a different form of audience participation exists due to the developments in interactive technology. Current technology is used to enhance the spectator's experience and enables the audience to interact with the performers and each other during live events. The BannerBattle experiment (Ludvigsen and Veerasawmy, 2010) explored how interactive technologies can support the spectators' experiences while occupying the stands in sports arenas. The BannerBattle experiment used cameras and microphones to track the movements and record the clapping sounds made by the crowd. The spectators' activity was converted to a video output displayed on screens in front of the fans of both teams. The fan group with the most physical movements and loudest sounds occupied most of the area of the screen display. Along the same line as BannerBattle, Barkhuus and Jørgensen (2008) used a cheering meter in improvisational rap competitions to detect the winner and show the results in four large screens. Being a part of a larger group and having a social experience, at the sporting event, means a great deal for the spectators. According to Fairley (2003), the spectator's identification with the other spectators might be an important factor in their engagement with the sporting event. In both of the above examples, the spectators were not actively involved in the performances, instead, their experience was technologically enhanced by having their responses translated into visual elements that were used as clear signals of communication to the performers and to the rest of the audience.

Another classical example is the Cinematrix Interactive Entertainment System (CIES) by Rachel Carpenter (Maynes-aminzade et al., 2002). In CIES, each audience member used the motion of turning a wand object one way or the other to participate in any type of event. Inspired by Carpenter's idea, several years later Aigner and his team (Aigner et al., 2004) used clapping and cheering as a way of measuring the votes of an audience in a sports event. The audience voting system made by Aigner and his group utilised natural activities such as clapping and cheering to acquire information from the spectators during the event. This low-cost system consisted of wireless wearable motion sensors and microphones that enabled spectators to cast their votes in real time. The readings taken from the sensors and the microphones influenced the score during an athlete's performance by being presented on wall-sized stadium displays.

A final example that fits well within the above ideas is Glimmer (Freeman and Godfrey, 2010), a composition tool that controls an orchestra through audience collaboration.

Glimmer used light sticks, video cameras, computer software, multi-coloured and stand lights to create a continuous feedback loop in which audience activities influenced the orchestral musicians on stage.

These are some of today's examples that incorporate different forms of audience participation in an event. While all the examples described above hold the audiences' attention during the event, they do so in especially explicit and consciously directed ways that are perhaps not always consistent with how they would "naturally" respond to a performance. However, this active involvement of the audience in the event usually tries to increase the engagement of the audience and as a result provides clear signals to the performers on how well the performance is going. This is in contrast to the traditional theatre seated audiences studied here, where in the majority of cases, have limited chances to respond during the performance while the performers control and dominate the performance space from a raised and artificially lit stage.

### 2.2.2 Seated Audience

Today, traditional theatre audiences have learned to follow a set of strict behavioural patterns: arriving before the beginning of the play, sitting in an allocated seat in the dark, remaining still and not talking during the play (Pasquier, 2015). In most live performances, the primary conventional opportunity for members of an audience to express their satisfaction or dissatisfaction about a performance is through applause and/or cheering.

Nonetheless, audiences have notoriously recruited other means of signalling their ongoing responses including the organised and carefully timed use of apparently innocent activities such as coughing (Wagener, 2012; Broth, 2011). According to Broth (2011) activities such as coughing and throat-clearing noises occur between scenes or between two sequences of action, at a time when the actors are not actually busy acting. Based on the analysis of four video recordings of shows at the Théâtre de la Colline in Paris, Broth (2011) found that the audience members tended to remain completely silent, and that those who made noise made a real effort, internally, to ensure that their timing caused as little disturbance to others as possible. Broth's study also found that audience members coordinated with each other to laugh at the same time. An individual who laughed alone would stop laughing if others did not join in. On the other hand, if other people's laughs mingled with his or hers, the laughter in the theatre increased, rising to a crescendo before stopping when the dialogue resumed.

A similar pattern occurs during applause sections. Mann et al. (2013), used a mathematical model to quantify the role of social contagion in the starting and stopping of applause. In an effort to predict how clapping spreads through an audience, they filmed the clapping response of six groups of university students during an oral presentation and found that both the onset and the pause of applause followed a sigmoidal curve similar to the ones that are very typically seen in the spread of diseases (Mann et al., 2013).

They also found that the rate in which new individuals started to clap, after the first clap was made, was proportional to how many people were already clapping. Finally, they showed that spatial proximity did not affect the time that people started clapping. The probability that an individual would start clapping increased relative to the number of other audience members that have already started clapping but it was not influenced by physical proximity.

These studies show that for individuals to form an audience in a theatre, each member of the audience unconsciously adjusts to the responses of the others towards the performers' actions. This is one of the main elements that characterises the live experience. Although many practitioners would corroborate the above observations, surprisingly little work has focused on studying these interactions. This thesis shifts its focus away from the stage and concentrates instead on the activities taking place in the auditorium which are in turn analysed. Notably, this thesis focuses on the especially restrictive case of contemporary dance audiences.

### 2.2.3 Dance Audience

Most of the existing research on dance audiences focuses on the distinction between expert and novice audience members (Vincs et al., 2010; Stevens et al., 2009; Calvo-Merino et al., 2005) or investigates audience responses to specific aesthetic elements of the dance performance.

The research of Vincs et al. (2010) investigated the engagement levels of novices and experts towards dance by collecting audience continuous self-reported data and motion capture data from the dancers. Their results show that dance experts responded with more sudden rises in average engagement than novice students. They called these sudden rises in engagement 'gem' moments and they defined them as time points where the average engagement increased by a minimum of 0.1 points in one second for one or more seconds. They speculate that in their study the dance experts might have responded with more gem moments because they were more active and skilled observers of dance and were able to see and appreciate more subtle movement detail than the novices. In the same study, Vincs et al. (2010) tested for any possible correlations between dancers motion data and audience engagement. Their results didn't show any consistent association between increased absolute velocity of dancers and increasing (or decreasing) engagement. In a similar way, Stevens et al. (2009) used eye tracking technology to measure the eye gaze of dance experts and novices during a dance performance. Their findings showed that novices had the tendency to fixate to the background while experts spent less time on the background and more time fixating on the head and torso regions of the dancers. They also showed that the overall durations of fixation of the experts were significantly shorter that those of the novices.

Vincs' work on audience engagement levels and where these correspond in a dance piece (Vincs et al., 2010, 2008) showed that periods of high engagement often followed choreographic surprises, and that periods of low engagement tended to be associated with more predictable dance routines. Similarly, Vicary et al. (2017) used a wearable device to measure heartrate variability and continuous self-reported enjoyment ratings in an audience watching a dance performance. Their results showed predictive relationships between performers synchrony and audience enjoyment ratings as well as between synchrony and changes in audience heart rate.

The existing research cases discussed above focus more on dance aesthetics and specific elements of a dance piece rather than on the elements that characterise the live experience which is the main focus of this research. This thesis shifts from the actual dance performance itself and the covert audience responses that might be individualistic and don't contribute to the experience of the live performance and focuses on the overt audience responses that might provide live feedback to the dancers and to the rest of the audience.

In particular, this research focuses on the genre of contemporary dance. Contemporary dance is a dance performance genre that developed during the twentieth century as a reaction against the rigid techniques of classical ballet and has become one of the dominant genres for formally trained dancers throughout the world. Martha Graham (1894-1991) was the first dancer who introduced and popularised contemporary dance to the worldwide audience (DanceFacts, 2012) while other pioneers were Isadora Duncan and Merce Cunningham. Technically, contemporary dance borrows elements from classical, modern and jazz styles. The major medium in contemporary dance is mainly the natural and free movement of the body that allows a fluidity of movement compared to conventional dance styles. As opposed to classical ballet, contemporary dance has no single vocabulary. All the movements in contemporary dance can be notated graphically via Labanotation (Griesbeck, 1996) (introduced by Rudolf Laban in the 1920s).

Contemporary dance may be inspired by a concept, human feelings, a space, a sound, a texture etc. It comprises movement, investigating how weight and force interact with time and space requiring no support from music, no visual background, no plot (Stevens and McKechnie, 2005). Overall, one should note that compared to other dance genres this abstraction and freedom that exists in contemporary dance can offer to the observers a multimodal sensory experience during which it is possible to experience visual, aural and even a kinaesthetic stimulation (see more details in section 2.4). Audience responses can vary depending on the dance genre, with some genres allowing the audience to dance to the music while others, similar to the case is analysed here where the audience is very restricted and dancing is not an option to express their engagement to the performance.

If dancing, laughing or shouting are not audience responses that might occur during a contemporary dance performance, what are the possible audience responses that might contribute to the experience of a live performance? How do audience members express their engagement or boredom during the performance?

## 2.3 Audience - Performer Interaction

The audience responses discussed above may be a few of the ordinary ones that contribute to the experience of the live performance. Apart from simply occupying the same time and space, the co-presence of audience and performers implies an active relationship between them. According to Garner (1994) it is not only the audiences that look at the performers but also the gaze of the performers is returned to the audience. Similarly, Fischer-Lichte (2008) describes how "performances are generated and determined by a self-referential and ever-changing feedback loop". This is again pointing to the mutual relationship between audience and performers and how that impacts upon both.

The live experience is different depending on the kind of the performance. This ongoing feedback can be especially obvious in cases such as stand-up comedy (Harris, 2017) or in concerts e.g. shouting, laughter and heckles or even dancing. However apart from the obvious signals of applause and laughter, performers talk about how they feed off the energy of their audiences and how this energy affects the level of their engagement in the action. They can distinguish between "good" or "bad" audiences for the same performance and between moments of engagement or "lift" and moments of boredom in an audience (Healey et al., 2009). Schechner talks about audiences collective and unconscious behaviour when they catch their breaths, shift position or become very still (Schechner, 1994).

An experiment carried out by Ravar and Anrieu (1964) indicated that actors were highly attentive to audience feedback. The authors made sound recordings of 30 performances of the same play – "Monsieur Biedermann et les incendiaires" at the Théâtre de Poche in Brussels – and then interviewed the actors. First, the recordings showed that the performances were not exactly the same: the audience did not always laugh at the same times, the silences did not have the same quality, and there were strong variations in the number and volume of sounds recorded (whispering, seats squeaking, coughing). The actors were interviewed following these recordings and said that all the noises made in the theatre were messages from the audience. In addition, they explained that silence is an indicator of strong emotion – hence a very good audience – while small noises of discomfort are interpreted as boredom, and isolated laughs without the rest of the audience joining in signify a misunderstanding of the script or the staging (Ravar and Anrieu, 1964).

In a typical contemporary dance performance which is the case studied in this thesis, the audience will be in the dark, while the performers will be behind bright lights with loud music, drowning out other sounds. In addition, the performers will also have to contend with the physical and cognitive demands of the dance performance itself. This places severe limitations on what the dancers are able to sense, even in principle, from the audience responses during a performance. According to the concert pianist Rosen (2002), apart from the moments when the audience misbehaves, this sense of the audience might be suppressed during this type of performances. For Rosen (2002), a cough is a basic sign of inattention and only at the end of the performance the audience can express a collective and noisy opinion.

A further limitation on the potential concurrent feedback between audiences and performers is introduced by the conventions about what forms of audience response are considered appropriate; laughter is rare and shouting and heckling are definitely out. This raises the question of what performers are detecting in these situations that feeds their ongoing sense of how engaged the audience is during a performance.

Although many practitioners would corroborate the above observations, surprisingly little work has focused on studying these interactions specifically in dance. This thesis shifts its focus away from the stage and concentrates instead on the activities taking place in the auditorium.

### 2.3.1 Liveness

Most of the research discussed above is focused around the concept of liveness and the definition of a live performance. In the wider sense, live was established in opposition to recording. This is something that Martin Barker (Barker, 2003) notices in his analysis of audience responses to stage and screen presentations of J.G. Ballard's Crash. Barker observed that his respondents frequently try to understate film in order to arrive at a social or cultural assessment of the live experience over the non-live. According to Barker (2003) what the audience sees on the screen and how they see it, has already been decided by the director and this is different from the physicality and the energy that an audience experiences in a live performance. During a theatrical performance, the act evolves in front of the audience and this makes them very important for the performers. For example, in theatre if the audience does not clap at specific times it may disrupt the flow of the performance, while in cinema if the whole audience leaves the room, it will not have any effect to the film.

Barkers findings are somehow related to Auslander's (Auslander, 2008) views which try to explain the essential and authentic experience of the live, versus the secondary experience of the non-live. Auslander describes the ways in which theatre uses a variety of mediating and technological devices into the productions which makes it hard to separate the live from the non-live elements of a live performance. One of his examples describes how young people at a live rock concert are able to watch large-screen, close-up projections of what is happening on stage, and even being able to listen with headphones linked directly into the bands' amplification systems. To Auslander, this clearly constitutes a failure of real liveness. His overall general argument, is that the live can only exist in a context where there is a recording. In other words, it is a category of the not-recorded (Auslander, 2008).

Reason (2004) focused on the experiential effects of liveness on real audiences. According to Reason (2004), in contrast to non-live performances on film or television, the attendance of a live performance and the concept of liveness are considered as a commodity that is purchased by audiences. Reason (2004) investigated the definition of a live performance using post-performance discourse analysis on a theatre audience. His participants' experience of a theatrical production is shown to be shaped by the diversity of the audience they were part of, and of the performers they watched. Perceptions of similarity and difference between those co-present in the performance space was often mentioned in their discussion. Reason notes that eye-to-eye and thigh-to-thigh contact is reinforced by the small of the venue where the study took place.

Most of the group conversations in Reason's discourse analysis show many elements that can contribute to the definition of theatre as live performance. Some of these include, discussions about the proximity between the audience and the actors, the sense of immediacy, the risk of an error during the show, the awareness of other audience members, a sense that other people are having a different experience, the sense that it is a single event never to be repeated and a feeling of community with other audience members.

The existing research presented above shows that the dynamics of interaction that occur among audience to audience and audience to performers is what creates this awareness of others during a live performance. Even though the type and intensity of interactions during a live performance may change depending on the genre, the venue, the size of the audience etc., attending a performance is a social event, resulting not just in the awareness of others, but also in an awareness of the personal responses of others (Harris, 2017).

In cases such as in dance which is the study subject of this thesis, these interactions might be pervasive and fine-grained, often requiring "micro" analysis to identify the cues of interaction (Bavelas et al., 1986). An intuitive example is gaze in an auditorium, where the eyes or head position may provide a sign to others of what is being attended to (Harris, 2017). Reactions to the performance are in part externally visible, and the understanding of such responses results in sensible reactions of others. A live performance is a result of feedback processes and is bound to their continuing operation. In essence, preconditions are defined, and then performance arises through interactional dynamics.

Overall, there is no clear definition of liveness and there is very little literature discussing what is actually going on during the performance. Research that emphasises co-present and considers performance as a social situation shows potential in engaging with the conditions of a live event. However, research that is based on a cultural analysis only seems less useful, by definition less generalisable and abstracted from these conditions.

## 2.4 Kinesthetic Empathy: Being engaged in dance

One of the most common concepts explored by dance researchers and psychologists is kinesthetic empathy. According to Calvo-Merino et al. (2005) affective responses to body movement can be explained in terms of "kinesthetic" proprioception. Kinesthesia or kinesthetic empathy refers to the awareness of the position and movement of the parts of the body by means of sensory organs in the muscles and the joints. When an observer watches a dance performance, it is possible that he or she translates the visual stimulation from the dancers into kinesthetic and visual images of himself or herself performing the body movements (Stevens, 2007).

The definition of Kinesthesia was introduced by the dance critic John Martin (Reason and Reynolds, 2010). Martin described kinesthetic empathy using a range of different terms such as "muscular sympathy" or "metakinesis". He also used the term contagion referring to the contagion of bodily movement that happens to someone who feels sympathetically in his own muscle system when he sees exertions in someone else's muscle system. Research by Reason and Reynolds (2010) which is based on Martin's theories relates kinesthetic empathy to spectators engagement with dance and argues that it can be a strong reason why people choose to watch dance performances.

Reason and Reynolds focus on ethnographic audience research which tries to identify a range of kinesthetic pleasures that spectators articulate, while watching different types of live dance performances. Their study included a sample of 150 audience members that the researchers tried to enter into discussion with, by providing circumstances where the audience could describe their experience of watching dance in their own words. The participants responded to some questions that were relevant to kinesthetic empathy while others related more to the social experience, musical engagement or to intellectual reflection. One of their findings showed that reported kinesthetic empathy varied depending on people's experiences with dance. This means that people with more experience in watching dance or even being professional or non-professional dancers reported more kinesthesia compared to the inexperienced ones. In addition, some of the participants' responses showed that for a number of spectators the lack of familiarity with a particular dance style or music, made it difficult to remember the details of a performance, while for other spectators this lack of experience may derive from lack of understanding which eventually leads to lack of enjoyment.

The "Watching Dance: kinesthetic Empathy" group (Jola et al., 2012) explored audience implicit responses during dance performances, using neurophysiological research (functional magnetic resonance images (fMRI)) to address research questions relevant to kinesthetic empathy. They argue that kinesthesia is central to a dance audience since spectators can experience movements without physically moving their bodies. Their results showed that kinesthetic response is more likely to be activated if the spectators are expert dancers and have the necessary skills to understand the observed movement.

Similarly, research by Winters (2008) explored the notion that people's emotions that involve body postures change depending on whether they observe someone perform a posture or if they perform the posture themselves. Participants in Winter's study were asked either to embody a posture or to observe a dance therapy student performing the same posture and write down for both cases the feeling that they associate with each posture. The results of the study showed that apart from the emotion of anger, people seemed to have the same emotional response whether embodying a posture or watching someone else perform the same posture. In the case of anger, participants tended to identify anger at a much higher level when embodying postures than when watching them.

Winter's results are in line with the premise of mirror neuron research, which states that the same neurological mechanisms operate both when embodying an action, as well as when watching someone embody the same action. Mirror neurons were originally discovered by Giacomo Rizzolatti and his colleagues at the University of Parma, in Italy, while studying the motor activities of monkeys. Mirror neurons fired, when a monkey performed an action as well as when the monkey watched another monkey perform the same action (Gallese, 1998). Although the evidence of mirror neurons in humans is very weak, it has provided a hypothesis of how humans perceive actions, how action perception is linked to kinesthetic modes of communication, kinesthetic empathy first and then empathy, as a mental state. The research on mirror neurons has been adopted by dance therapists because by activating their patients' putative mirror neurons they can create a stronger therapeutic relationship between themselves and the patient.

In an experiment by Jackson et al. (2005), fMRIs were taken of individuals observing photographs of human hands and feet in painful positions. When looking at these pictures, it was observed that the area of the brain associated with pain was activated. Similarly, De Gelder (2009) also used fMRI technology to observe peoples' responses to images of bodily postures of fear. It was found that when viewing these images, areas of the brain known to be associated with emotional processing were activated. However, it has to be said that in both cases the results do not provide evidence of mirroring but of correct interpretation.

Finally, Calvo-Merino et al. (2005) worked with groups of people that had different acquired motor skills to investigate whether the brain's system for action observation was tuned precisely to the individual's acquired motor repertoire. If this was true, then the premotor and parietal cortex activity should be stronger in individuals who when observing a given action knew already how to perform that action compared to those who did not. They tested this hypothesis using an fMRI in which expert ballet and capoeira dancers watched videos that consisted of both ballet and capoeira movements. In this way, both groups of experts saw identical action stimuli, but only had motor experience of the actions in their own dance style. During the experiment, each video was repeated four times and subjects were instructed to indicate how tiring they thought each movement was by pressing one of three keys with three fingers of the right hand. The results showed that experts had greater activation when observing the specific movement style that they could perform. While all the subjects in the study saw the same actions, their brains responded quite differently according to whether they could do the actions or not.

The methodology used by Calvo-Merino et al. (2005); Jackson et al. (2005); De Gelder (2009) on testing kinesthesia focuses on the covert brain responses of participants and not on the overt body movement that is the main focus of this thesis. Therefore, it can be argued that kinesthesia is a covert experience that cannot be detected by external observation. The concept of kinesthetic empathy as described in Reason and Reynolds (2010) defines kinesthesia as an internal process connected to pleasure and affect. Spectators in Reason and Reynolds (2010) research talk about the effects on the body, imagination and feelings that result from watching the movement of others. This view effectively renders kinesthesia irrelevant for our pragmatic hypothesis of audience-performance interaction. Therefore, mimicry or contagion might lead to the replication of overt audience movement based on the movement of the dancers. This concept of mimicry or movement simulation will be tested in this thesis as it may suggest one possible way in which audiences and performers could be connected or communicate during a dance performance.

## 2.5 Forms of Engagement and Boredom

The first two sections described the basic context of an audience in live events with the final two sections focusing on dance audiences and audience-performance interaction. The following sections will first give an overview of the term engagement, beginning with audience engagement during a dance performance, then followed by non-verbal cues of engagement taken from literature of psychology and human computer interaction.

### 2.5.1 Definitions of Engagement from Human Computer Interaction

There is currently no accepted theory of what audience engagement and/or boredom is, partly due to conflicting definitions. The term engagement is being used in a number of diverse research domains, scientific as well as commercial. However, most of the research on engagement comes from a Human Computer Interaction (HCI) context and in particular from the interaction of a single user with a piece of technology. There is much variability and often vagueness in respect to what exactly the term engagement means. For example, a number of related concepts, such as interest, sustained attention, concentration, immersion and involvement, are sometimes used interchangeably and how they actually relate to engagement is often unclear. In the literature, engagement is mentioned in a number of different ways: as a process; as a stage in a process, as an experience; as a cognitive state of mind; an empathetic connection; as a perceived or theorised indicator describing the overall state of an interaction.

According to the model of engagement by O'Brien and Toms (2008), individuals can have focused attention but not for long, stable periods of time. O'Brien and Toms explored engagement in four application areas: web searching, education, webcasting and video games. They conducted semi-structured interviews with 17 participants and showed that engagement is a process comprised of four distinct stages: a point of engagement, a period of sustained engagement, disengagement, and finally reengagement. People may cycle through these stages of engagement several times during a performance or during their contact with technology. It is a natural starting point to consider that engagement consists of at least these four broad phases. However, what triggers each of these phases as well as the duration of each phase is unknown. According to Brien's model, disengagement is provoked by both external and internal factors. Individuals may consciously stop their activity because they've lost interest or feel pressure because of time or because they need to do other things. The external factors can be lack of novelty of the technology that is being used or usability problems (O'Brien and Toms, 2008).

Another definition of engagement in HCI is by Chapman et al. (1999), who related engagement with attention. He pointed out that something that engages us is something that attracts and holds our attention. In his research in multimedia training systems, Chapman et al. (1999), divided engagement in passive or less passive (controlled or active). Using definitions from cognitive psychology, he argued that engagement is more passive when individuals have their attention captured but there are no responses to inputs, while less passive engagement requires less effort from the person to become involved into the activity. However, engagement and attention are related but not equivalent. Attention can mediate instantaneously between many competing stimuli, while engagement lasts longer, it is not as completely exclusive, and implies at least a partial commitment to action (Henrie et al., 2015). It is possible to have attention without engagement, and engagement without attention. Driving a car while day-dreaming is an example of attention with minimal engagement, while introspecting on the implications of a lecture you are currently attending is an example of high engagement without paying second-by-second attention.

Immersion is another term that has similarities with engagement. According to Peters et al. (2009), during engaging situations when playing computer games, experiences relating to engagement have been reported as feelings of losing oneself in the world of the game, not noticing things happening outside of the screen, or losing all track of the passage of time. These experiences are often related to the concept of immersion, and engagement has been described as the first of three levels of immersion, where the user is required to invest time, effort and attention in learning how to play the game and get to grips with the controls.

Finally, Read et al. (2002), presented engagement as one dimension of fun, together with endurability and expectations. The authors measured children's fun when participating in an event using video footage that was then analysed with reference to a set of positive (engagement) and negative (disengagement) instantiations. The positive instantiations that the researchers were looking for were smiles, laughter, concentration signs (fingers in mouth, tongue out) excitable bouncing, and positive vocalisation. Negative instantiations were frowns, signs of boredom (ear playing, fiddling) shrugs, and negative vocal instantiation. However, they didn't validate that these instantiations really correlate with engagement or disengagement respectively.

Overall, it is noticeable that user engagement with technology differs from audience engagement during a live performance. All the definitions described above are very individualistic and they are only able to consider what happens when one person interacts with a piece of technology. However, engagement in the context of an audience should be supported by a relation between two (or ideally more) people. If only one member of the audience is engaged during the performance then it would not sensibly count as engagement. In addition, while we might find a common ground in the moment where people may become engaged in the first instance as defined by the (O'Brien and Toms, 2008) model, it is hard to identify when disengagement moments occur during a performance mainly because there is no task involved. An audience's task during a traditional performance is to sit quietly and watch the performance without talking, coughing or moving. Since audience responses are very restricted during a contemporary dance performance the only available channel of communication from audience to dancers but also from dancers to audiences is body movement. Thus, it is expected that audiences can only unconsciously express their engagement or disengagement to the performance using their bodies. This statement leads us to the sections that follow and which will form the baseline of this thesis.

### 2.5.2 Non-verbal cues of boredom and engagement

A number of attempts have been made to set up typologies of non-verbal behaviours based on the frequency of their occurrence, the part of the body involved, their formal aspects, relatedness to speech, etc. Existing research suggests that both boredom and engagement are associated with specific body postures, including the expressions of the face, the position of the head (D'Mello et al., 2007; Witchel et al., 2014b; Bull, 1978) torso (Grafsgaard et al., 2012) and hands. Non-verbal interaction plays a significant role in how humans communicate and empathise with each other. The ability to understand non-verbal cues is important to recognise and analyse the actions and intentions of others (Calvo et al., 2015). The human body is today often regarded as a channel of interpersonal communication, conveying information relating to emotion and interpersonal attitudes (Bernhardt, 2007). This section presents work that is relevant to the ways people communicate though facial expressions, body posture, movement and gesture and how these non-verbal cues are connected to engagement and boredom. The section is divided into three subsections, each subsection outlines existing research in non-verbal behaviour of the face, the body and the hands and explains how these can be interpreted as forms of engagement or boredom.

**Face**

The most obvious way one can measure explicit audience responses is by analysing their facial expressions. Most of the literature about facial expressions comes from the area of HCI and affective computing, which focuses more on the creation of algorithms that recognise specific emotions rather than trying to identify when and why these emotions occur. The well-known study of Friesen and Ekman (1978) formed the basis of visual facial expression recognition. Their studies suggested that anger, disgust, fear, happiness, sadness and surprise are the six basic prototypical facial expressions recognised universally. However, there is very little research relevant to facial expressions and engagement or boredom.

The BBC [1] is developing plans to apply new facial coding technology – revealing viewers' subconscious "emotional attachment" to programmes. Developed by a British start-up, CrowdEmotion, the technology uses cameras to record individuals' expressions and actions. Facial movements are recorded on a second-by-second basis and the results are divided into six possible emotions: sadness, puzzlement, happiness, fear, rejection and surprise. Similarly, Whitehill et al. (2014) research looked at ways to measure student engagement in classroom when students are using a PDA. They explored approaches for automatic recognition of engagement from the students' facial expressions by first studying whether human observers can reliably judge students engagement from the face when students were playing games on an ipad. They found that human observers reliably agreed when discriminating low versus high degrees of engagement.

Both of these studies however differ from the case we study here, mainly because users in these studies are interacting with a piece of technology rather than being in a live event sharing the space with other audience members but also with the performers. During a live performance, the audience facial expressions depend a lot on the social context and cannot be interpreted in isolation by measuring the movement of the mouth or the position of the eyebrows only.

According to the emotional expression view, a smile is the major component of a facial display associated with and caused by feelings of happiness or joy. Anything that makes a person feel good or happy should produce a smile unless the individual wants to mask or inhibit this display. Laughing is considered to be the expression of either more intense happiness or a particular type of happiness (Friesen and Ekman, 1978). Thus, when a smile does occur, the message is usually happiness (Friesen and Ekman, 1978),

[1] BBC advertising's "Science of engagement": https://www.bbcglobalnews.ltd/insights/science-of-engagement/

although this may be a false message if the sender is masking another emotion with a smile or if the sender is simulating happiness for some other reason. It is important to note that researchers who support this view have rarely studied such communication in natural social settings by studying the causes and consequences of smiling; rather, they have focused on the recognition and verbal labelling of emotions in facial expressions, generally in still photographs.

The role of gaze in dialogue has already shown that we look not just to see, but to be seen looking (Goffman, 1949). One approach to explore this is to test if a human response is only present when there is somebody to direct it to. Studies have demonstrated smiling as communicative behaviour using this approach. Observing bowlers, Kraut and Johnston (1979) reported that out of 116 bowls thrown by 34 people, there were 36 smiles seen, the majority directed towards friends, in contrast to 4 which were not. Kraut and Johnston (1979) coded 1793 four second sequences after a bowl for various behaviours and whether it was a good score, a temporal co-occurrence analysis of smiling with other behaviours and a principle component analysis of similarities of co-occurrence both suggest that bowlers smiled when they were being social, when they were being playful, or when they were otherwise communicating an emotional statement to an audience. According to the emotional hypothesis, bowlers should smile whenever they feel happy, for example immediately following a spare or strike. But according to the social hypothesis, smiling occurs during social interaction, and the score obtained is irrelevant. To avoid any biased results Kraut and Johnston (1979) also tested lone bowlers and found that they rarely showed any facial displays but instead maintained a generally neutral face. The most common expressions seen were relatively antisocial or negative—looking down, tight lips, and negative exclamations; they rarely smiled.

In another study, Kraut and Johnston (1979) reported similar findings obtained by coding photographs of ice hockey stands full of fans. It was recorded that people smiling when in a social group raised to 23% versus 6% when just facing the game. These photos were taken immediately following events that were favourable, neutral or unfavourable to those fans. In total 3726 faces were coded, and grouped into those identified as in or not in social units (with one member facing the others and not the game). Finally, in a study on pedestrians, social interaction was found to be a much more powerful predictor of smiling when the weather was nice rather that when it was not. In all these cases, a social motivation for smiling was compared to an emotional elicitor, and social involvement was found to be a far more important cause of smiling, independent of the emotional elicitors.

Correlating presumed emotional elicitors with other phenomena does not mean the emotional state of all the people being compared is consistent, or even known. Fernandez-Dols and Ruiz-Belda (1995) addressed this by conducting a study of facial expressions at one of the happiest times of an athlete's life: being awarded an Olympic gold medal. Observers, including other Olympic gold medalists, judged the emotional experience of the athletes to be that of intense happiness throughout the ceremony. As the ceremony included two stages that restricted any social interaction surrounding a section where the athletes interacted with the authorities and public, a comparison could be made. The results showed that the duration of smiling in the interactive session was higher (duration of smile =47.75sec) compared to the non interactive ones (duration of smile in session A=2.76sec and in session B=0.00sec). In summary, this study also found happiness not sufficient for smiling, but an interactional situation makes smiling much more likely.

Even when alone, smiling has been shown to be better predicted by social context than reported emotion. Through experimentally manipulating the presence of a friend, Fridlund (1991) reported that smiling increased with the sociality of viewing but not with reported emotion. Sixty-four participants viewed a pleasant video either alone, alone but with the belief that a friend nearby was otherwise engaged, alone but with the belief that a friend was viewing the same videotape in another room, or when a friend was present. The participants facial behaviour was measured using electromyography on the muscles responsible for smiling. The participants' emotional state was self-reported before and after the viewing using forms to score the extent to which various emotional states were felt. The results agreed with the studies above for the lone participant and for the explicit audience conditions. The novel enquiry and subsequent result of the study was that an implicit audience also had an effect. Equal "smile" muscle activation occurred in the mere psychological presence of a co-viewer as with the direct presence of a co-viewer.

This section suggests a strong association of smiling with a social motivation and an erratic association with emotional experience. This is something this research examines in the context of a live audience. Do audiences display their reactions selectively only during social interaction or do they express their emotions with animated facial expressions during the performance?

### Body

Psychologists such as Bull (1978); Kendon (1990) and more recently computer scientists such as Kleinsmith have demonstrated that static body posture can communicate affect for contexts such as conversations or expressively acted emotions. According to Bull (1978) there are specific head positions that characterise boredom such as when the person's head drops, turns or leans sideways. However, there is no clearly articulated association between postures and their interpretation. Some psychology theories (Pease and Pease, 2004), and many scientific studies on interpreting non-verbal behaviour (James, 1932; Coan and Gottman, 2007; Rodrigo and Baker, 2011; Sanghvi et al., 2011), have suggested that leaning forward when sitting is a postural marker of engagement. On the other hand, several studies that measured averages of head distance-to-screen do not support this proposal (Mota and Picard, 2003; Witchel, 2013; Witchel et al., 2014b). The studies that disagree instead pointed out that forward-leaning load-bearing postures, where the head rests on the hands, are usually associated with boredom, disengagement, or difficulty, despite the fact that these postures are invariably associated with more forward leaning than most other seated postures. The use of body position as a marker of engagement remains controversial except when detecting outright sleep (e.g., during night driving). According to Witchel et al. (2014b) body posture alone is not a sufficient marker of engagement and also depends on the kind of stimulus and interaction needed.

Apart from body posture, body movement is another measurement that has been used to identify engagement and boredom. Most research in HCI suggests that the increase of overall body movement is related to boredom and frustration while diminished movement is related to engagement (Kapoor et al., 2007; D'Mello et al., 2007; Grafsgaard et al., 2012). Kapoor et al. (2007) found that head velocity was a reliable indicator of self-identified frustration in 12–13-year-old children working on a computer version of the Towers of Hanoi puzzle. D'Mello et al. (2007) included increased change rate in seat pressure as an indicator of boredom during a physics learning session with an automated tutor system. Grafsgaard et al. (2012) tested a computer-mediated human-human tutoring system for teaching Java to university students and found that diminished head movement was related to engagement, and that increased overall body movement was related to frustration. Woolf et al. (2009) studied children's behaviour in a classroom using a mathematics intelligent tutor, and found that high levels of head movement were correlated with negative valence, high arousal, off-task behaviour, and non-desirable states.

All the above studies measured engagement during the interaction between a user and technology where specific tasks were performed. For passive tasks like the one explored in this thesis there is no coherent definition for engagement and/or boredom and research shows that they could both be performed in a stare of high or a low activity state. Restless activity includes fidgeting or stunted escape efforts while lethargic boredom might manifest in the viewer resting their head on their hand with elbow support (load bearing). A similar argument holds for engagement: dynamic engagement could be a football fan raising their arms in celebration of a goal, while rapt engagement might be a child watching a cartoon in perfect stillness (Witchel et al., 2014b). This suggests that body speed might be a useful way to distinguish between engagement and boredom but in passive tasks like the ones examined here such indications have to be studied more carefully.

According to one theatregoer interviewed by Pasquier (2015), the audiences' increased body movement shows disengagement. The 68 year-old theatregoer says the following:

> "When one's concentration goes, the body needs a release, by crossing one's legs, sitting up on one's chair... and coughing of course. That's the cacophony of failure. One senses the dispersion, people who start moving, changing position, who're leaning like this on their hand, who dip their head or look at others, you feel they're thinking 'shit, this is never going to end', who look at their watch, so it does show. I've got antennae..." (Pasquier, 2015)

It seems that increased fidgeting in an audience has been commonly defined as a general indication of boredom, irritation, and lack of attentional engagement (Seli et al., 2014). In an early test of this claim, Galton (1885) observed fidgeting behaviours by the audience members during a rather boring lecture. Galton (1885) observed that when the audience was more engaged the frequency of fidgeting reduced by more than half and the duration of each movement also reduced.

> According to (Galton, 1885), when the audience is intent each person forgets his muscular weariness and skin discomfort, and he holds himself rigidly in the best position for seeing and hearing. But when the audience is bored the several individuals cease to forget themselves and they begin to pay much attention to the discomforts attendant on sitting long in the same position. They sway from side to side, each in his own way and the intervals between their faces which lie at the free end of the radius formed by their bodies with their seats as the centre of rotation varies greatly.

In a more recent study based on Galton's observations, Witchel et al. (2014b) investigated potential links between fidgeting and mind wandering. Specifically, Witchel et al. explored the hypothesis that, at least under conditions of mildly restricted movement analogous to the lecture context in Galton's study (the performance or the classroom), mind wandering may be temporally associated with increased fidgeting. They found that the participants' movements were greater during mind wandering than during on-task performance. The results therefore suggest that mind wandering is related to increased fidgeting, both in terms of observable behaviour and at a self-reported individual level.

One might imagine, however, that if an objective task requires one to sit still (e.g. listening to a lecture, watching a performance), episodes of mind wandering may result in increased fidgeting behaviour, whereas if an objective task involves continuously moving about in a variable fashion (e.g. driving a car or playing a videogame) movement might decrease during episodes of mind wandering. This suggests that mind wandering might result in behaviour that comes in contrast to one's external goals and that it may even be associated with a form of behavioural regression. When mind wandering occurs, behaviours that are different to the requirements of the task are engaged.

For example, when driving, it is common practice for the driver to move his/her eyes and head frequently; that is, he/she must constantly observe the road ahead, as well as check for relevant signs, pedestrians e.t.c. It is a common informal observation however that people tend to decrease these driving-related movements during mind wandering and enter a state of stillness, displaying a blank stare and a lack of eye movements. An opposite example would be fluctuations in eye movements in line with lexical variables during reading that tends to diminish during episodes of mind wandering (Seli et al., 2014).

In summary, the claims in the literature about the relation between body moments and engagement or boredom are not entirely consistent and seem to depend a lot on the social context of the activity. However, based on the literature presented above it seems plausible that in the context of a live contemporary dance, the audience body movement may indeed give out information about audience engagement or boredom to the performance.

#### Hands

There is no existing research that looks specifically at the relationship between hand gesture and engagement or boredom. Most of the literature has focused on explicitly designed co-speech gestures, however the content of this research includes the challenging case of gestures that are not directly related to speech.

According to McNeill (2008), all gestures are movements, but not all movements are gestures. A gesture is a movement that communicates information, intentionally or not (McNeill, 2008). Gestures are usually separated into the following categories: **a.** emblems, **b.** illustrators and **c.** adaptors (Kendon, 1983). Emblems are gestures that convey meaning by themselves and are assumed to be performed by the speaker on purpose. Illustrators are gestures that accompany the speech. They can further be distinguished into deictic, iconic and metaphoric gestures (Calvo et al., 2015). Deictics consist pointing towards a concrete object that has been materialised in front of the speaker. Iconics and metaphorics are gestures that represent derived features of an object or an action, such as drawing a square to represent a frame or mimicking writing. Iconics describe concrete objects and actions while metaphorics represent abstract concepts. A gesture may also convey additional information, although such information is not strictly related to speech. A different division of illustrators was done by Bavelas et al. (1992) who divided illustrators into topic and interactive gestures. Topic gestures depict semantic information directly related to the topic of discourse and interactive gestures refer to some aspect of the process of conversing with another person. To be an interactive gesture it must have a paraphrase that is both independent of the topic and addressed to the visual presence of the interlocutor. Bavelas et al. (1992) studies showed that interactive gestures happen only in the existence of an interlocutor while the topic gestures are independent of the existence of a listener.

The final category, is the self-adaptors or self-touching gestures (STGs), these are gestures performed physically to make one feel better. They involve one part of the body doing something to another part of the body such as scratching one's head, stroking the chin, hand-to-hand movement, lip licking and fixing hair. According to Ekman and Friesen (1972), STG's occur more when the person is in private, and are less common in a public place. They are never deliberate, and receive little direct attention or comment from others. The latter is the category of gestures that we are interested in this research as these are the ones that don't accompany speech. STG's appear to lack overt, intentional design and may be performed with little or no awareness Harrigan et al. (1987). According to Harrigan et al. (1987), 55% of STGs are applied to head or face, 8% are applied to the legs and 2% of STGs are directed to the trunk.

According to Knapp et al. (2013) self-touching and manipulation of small objects occur typically due to boredom or negative attitudes towards others. Studies have shown that there is an increase in STGs in stressful and fearful situations (Butzen et al., 2005; Heaven and McBrayer, 2000) although Ekman and Friesen (1972) suggested that STGs may also occur when a person is relaxed. Butzen et al. (2005) found a significant increase of STGs in response to a video about chiggers compared to another kind of video about "wild turkeys".

In a study from Heaven and McBrayer (2000) the participants listened to texts about leeches and canaries and then had to answer several questions. Although there were no differences between the two listening conditions there was an increase in STGs for the leeches text during the answering period. Rogels et al. (1990) found that children between 3 and 6 years showed more STGs while talking about a cartoon they had just seen than while watching the cartoon. Other studies (Grunwald et al., 2014) hypothesise that there is a relationship between the frequency of STGs and arousal. Barroso and Feld (1986) investigated this by testing the occurrence of STGs performed with one or both hands as a function of four different auditory attention tasks. They found that with increasing complexity and attentional demands both one and two handed STGs increased.

Handedness also appears to play a role. It is now well-established that the two cerebral hemispheres are not functionally equivalent. In most right-handers, the left hemisphere plays the dominant role in speech and other aspects of language, while the right hemisphere is dominant for a variety of spatial functions (Hampson and Kimura, 1984). There is evidence that people use their right and left hand for different reasons while talking. According to a study on the behaviour of a French politician (Calbris, 2008), there was an increase on the use of the left hand when the politician was talking about the left-wing party or the opposing party (right hand).

There are no existing studies that test hand asymmetry for self touching gestures independent from speech or a specific task. Hampson and Kimura (1984)'s study measured the frequency of movement on right handed subjects while they assembled blocks to perform a series of verbal and non-verbal tasks. The results showed significant differences between the frequency of movement of the right and the left hand but only for movements that played a functional role in the performance of the task. For the majority of such movements, verbal tasks elicited a greater proportion of right-hand use, while non-verbal tasks elicited a greater proportion of left-hand use. During these tasks approximately 8% of all movements were self touching gestures. However, the results on the frequency of STGs did not show any significant change in asymmetry across tasks while the left hand was constantly slightly preferred for this type of activity. According to Hampson and Kimura (1984) this was not surprising, since self-touching movements were assumed to be unrelated to task performance. Similarly, in a study about natural speaking Kimura (1973) showed that right handed participants performed STGs equally as often with the left as well as the right hand.

Kipp and Martin (2009) found an association of handedness with the emotional dimensions of arousal. In particular, they found that the right hand is used more when experiencing anger and the left hand when experiencing relaxed and positive feelings. According to Roether et al. (2009) the body seems asymmetric in its emotional expressivity, with the left hand using higher energy and higher amplitude for emotional movements.

Hand behaviour and boredom is another relationship that might be useful in interpreting audience hand movements. According to Kroes (2005) bored people also tend to use their hands to support their head or perform STGs (rubbing or clutching face). However, Kroes notes that this hand behaviour is a sign of low arousal but it might not be a sign of dissatisfaction.

Overall, it seems that the research on the interpretation of gestures and hand movement that are not related to speech is still at a prelimary stage. However, it appears that STGs are implicated in the regulation of emotional and cognitive processes and in this research are considered as a possible audience response that might be detectable by the dancers.

## 2.6 Summary

In this chapter, the research topic of this thesis has been placed in the context of performance studies, human computer interaction (HCI) and psychology. A brief overview of each research area has been provided. A thorough review of existing audience research with a focus on dance audiences has been presented, and a representative selection of the term engagement has been described and discussed in detail.

The chapter began with a description of the nature of a live audience and its division in the categories of a participating and seated audience based on the kind of participation and on the forms of response that are allowed during a live performance. The members of an active audience are actively participating in the performance either using an unruly, disruptive behavior or by directly intervening in the play. In the same category the technologically enhanced type of performance was added, in which technology aims to improve the experience of the audience. On the contrary, the seated traditional audience, which is also the case studied in this thesis, does not have as many opportunities of response during a performance apart from the most obvious: the applause at the end. However, existing research suggests that seated audiences can have other forms of response during performances such as coughing. Even though there is no clear evidence that performers are able to continuously detect audience responses during the performance, there is evidence that after the performance, they are able to characterise whether the audience was engaged or not after the performance. A dance audience is a very restricted case of a seated audience where the communication between audience and dancers is even harder. However, there is a strong case to say that even during a dance performance audiences unconsciously use their bodies to show subtle signs of engagement or boredom.

Since overt audience responses are the only possible way of communication between audience and dancers, the final section of this chapter focused on the existing research of non-verbal cues of engagement and boredom. Due to the lack of existing research on overt audience response during a performance, the final section presented work that is relevant to the ways people communicate though facial expressions, body posture, movement and gesture and how these non-verbal cues are connected to engagement and boredom. Based on critical assessment of the different definitions of engagement and boredom, the interpretations of the results will be carried out in the discussion chapter.

# Chapter 3

# Live audience response metrics

## 3.1 Overview

This chapter describes the methodological approach followed in this thesis. It starts by briefly explaining the main reasons that the collection of continuous data from real theatrical settings was chosen and then presents the existing methods that have been used to measure audience responses during a live performance. The chapter closes with a brief description of the data collection methods used in this research as well as a description of the core principles of the methods used to analyse the data.

## 3.2 Continuous audience responses

The traditional approach of collecting audience data employs post-performance tools such as questionnaires, focus groups and audience interviews (Pasquier, 2015; Stevens et al., 2009; O'Neil et al., 2014; Walmsley, 2011). These methods are mainly used by audience researchers coming from a performance or cultural studies background but are also applied in the market research field from advertising and cultural organisations.

However, the use of post-performance tools as a primary method for data collection has the disadvantage of the "peak-end" effect, which shows that a measure taken immediately after an experience is strongly influenced by the emotion felt at the end of the performance (Latulipe et al., 2011). Such self-reported methods are easy to administer and yield much information but they rely on observer memory and do not allow for an understanding of moment-to-moment fluctuations in the responses that may occur as a performance unfolds.

More specifically asking people after a performance whether they liked it or not can be problematic, since whilst interviews provide evidence of the audience general impressions they do not offer data which represents what they actually do during the performance. In addition, post-performance tools are unable to measure continuous audience-to-audience and audience-to-performers interactions which characterise a live experience and are a central focus of this research. Open-ended, unstructured interviews can offer a detailed account of an individual's social world but the data is limited by what people are willing and able to say (Baker and Edwards, 2012). Semi- structured interviews offer comparability between participants and can be more easily delivered and analysed for a large number of people, but the data returned will be confined by the scope of the questions asked. If we want to know what people do then we must observe them or, even better, record them (Baker and Edwards, 2012).

In order to account for the dynamic experience of the performing arts, research suggests the use of momentary, continuous rather than discrete, post-performance measures to capture audience reactions as the performance unfolds (Schubert et al., 2009). These continuous measurements provide new potential for quantitative analysis, offering different perspectives to the more traditional approaches of understanding audience responses. Thus, finding ways to measure moment-by-moment audience engagement in real theatre settings is essential for getting a better understanding of the live experience.

A performance unfolds in time, making data collection problematic (Schubert et al., 2009), therefore a growing number of studies in dance research use motion sensing technologies primarily to examine dance movements (Calvo-Merino et al., 2005). In contrast to this, very little research has focused on audiences (for exceptions see e.g., Healey et al. 2009; Stevens et al. 2009; Vincs et al. 2010; Gardair et al. 2011; Jola et al. 2011; Latulipe et al. 2011; Mann et al. 2013; Katevas et al. 2015; Theodorou et al. 2016; Vicary et al. 2017). A description of the continuous metrics that have been used up to date will be provided in section 3.4.

## 3.3 Why "In the Wild"?

One of the main priorities of this research was to collect continuous audience and dancers data in real theatrical settings and not in a laboratory. This decision is motivated by the notion that the social behaviour of audiences and dancers will be influenced by the environment. Removing dancers and audiences from their "natural" environment might lead to changes in their behaviour. Social actions and identities are contextual and transferring participants to a laboratory to make a controlled study removes this context. These limitations appeared in a lab study by Harris (2017), on audience dynamics during stand up comedy where the recruited audience members were not classical comedy fans and ended up reacting in an unnatural way and focusing on the wrong things, with the added effect of the comedian not enjoying performing in that setting.

Setting up a dance performance with a recruited audience in the lab which lacks most elements of a traditional theatre might be just as unsuccessful since dancers are used to performing on a stage under strong lights and music while audiences are used to sitting in the auditorium in the dark. Performers are used to being observed while most of the times the audience chooses to attend a performance for purely observational entertainment. This relationship between observer and observed disappears in a lab setting where the audience knows that they are also being observed and may thus respond in an unnatural way.

On the other hand, conducting audience research "in the wild" is a complex task with many uncontrollable variables like the types of performance, the sizes and types of venue, and different audience populations. For example, one might think of performances that take place in non-traditional theatres where there is no clear distinction between the stage and the auditorium and the distance between performers and spectators is diminished. One might argue that audience responses might change depending on the type and the size of the theatre - i.e. the distance between audience and performers may influence their interactions, and thus the dance performance. These are interesting questions and might provide interesting information about the spatial aspects of the theatre space but are out of the scope of this research. The main focus of this research is to measure audience responses in traditional theatrical settings from audience members that have chosen to attend a particular dance performance.

## 3.4 Ways of measuring the audience

There are many possible ways to collect continuous audience responses in the performing arts and a variety of quantitative and qualitative measures of audience responses have been tried. These can be divided into overt responses expressed by visible human actions, movements or expressions and covert responses, those that can be expressed through biochemical and electrical changes in the human body but which can not be detected by an observer.

Some of the overt measurements include facial expressions (Katevas et al., 2015; Theodorou et al., 2016), body movement (Healey et al., 2009; Gardair et al., 2011; Theodorou et al., 2016; Vicary et al., 2017), eye movements (Stevens et al., 2009) and continuous self-rated engagement (Vincs et al., 2010; Vicary et al., 2017) while some examples of covert responses that have been used are brain activity (Calvo-Merino et al., 2005; Jola et al., 2011), galvanic skin response (GSR) (Wang et al., 2014; Latulipe et al., 2011) and heart rate variability (Vicary et al., 2017).

In the next two sections, existing methods that have been used to measure physiological and behavioural audience responses in the performing arts will be presented.

### 3.4.1 Physiological metrics - Audience covert responses

An audience response is defined as covert when it is unobservable, private and, in this particular case, not visible to the performers. Any response such as a change in peoples' heart rate, blood pressure, pulse rate, brain waves and skin conductance is considered a covert response. Most of these measures require specialised, expensive sensors and are difficult to use in large-scale studies.

In the past, collection of physiological measurements in audience research was usually carried out in a laboratory, where during an experimental session an individual would watch a recording of a performance. This was mainly due to the fact that such sensors with good enough quality were very expensive and thus difficult for the researchers to acquire, especially for a whole audience.

An additional limitation was that it might not be efficient to extrapolate from an individual's experience watching a recording to a larger audience watching a live performance given that being part of a live audience is a group experience. With today's technological improvements and new equipment the collection of physiological data in real theatrical settings from more that one audience member has become more feasible.

Galvanic skin response (GSR) is one of the cheapest and most common techniques that have been used when people tried to measure audience arousal (Lang, 1995). GSR is a common biometric that measures the conductivity of the skin through sweat, which is secreted in response to autonomic nervous system arousal. It has been recognised that increased GSR can be provoked by attention-related stimuli or tasks (Wang et al., 2014). GSR has historically been used in lie-detection, and more recently for measuring experience when playing video games (Mandryk and Atkins, 2007).

In order to explore if GSR is a valid measurement of engagement, Latulipe et al. (2011) recruited 49 participants (18 male, 31 female, all students) to watch a video of an 11-minute dance performance. Each participant watched the video individually. They wore GSR finger-wraps on two fingers of their non-dominant hand, leaving their dominant hand available to rate their engagement with the performance using a physical slider. Since each participant took part in the study individually and the performance was recorded, the study was not able to capture any of the social aspects of the live experience which are an important element of this research.

Wang et al. (2014), developed their own equipment (see image 3.1) and measured galvanic skin response (GSR) of an audience during a live performance. They measured the GSR measurements of 15 people watching a live theatre performance simultaneously. They also filmed the audience and the performers and synchronised the GSR measurements with the footage. Actors devised and performed a comedy that was aimed at audience participation and produced occasional "shocks" (e.g. a popping balloon) to elicit the occurrence of GSR spikes during the performance. The audience also filled in pre and post-performance questionnaires designed to evaluate the emotions that the performance evoked. They then compared the survey results with the GSR reading and showed that the use of GSR as a measure of engagement is valid, as the data accurately reflect the engagement of the audience members.

However, as seen in the figure below the spikes in the GSR data during the balloon popping were also visible on the video footage of the audience (e.g peoples' faces look surprised). This supports the idea explored here that audiences provide visible feedback, which in contrast to the GSR measurements is overt and potentially visible to the performers.

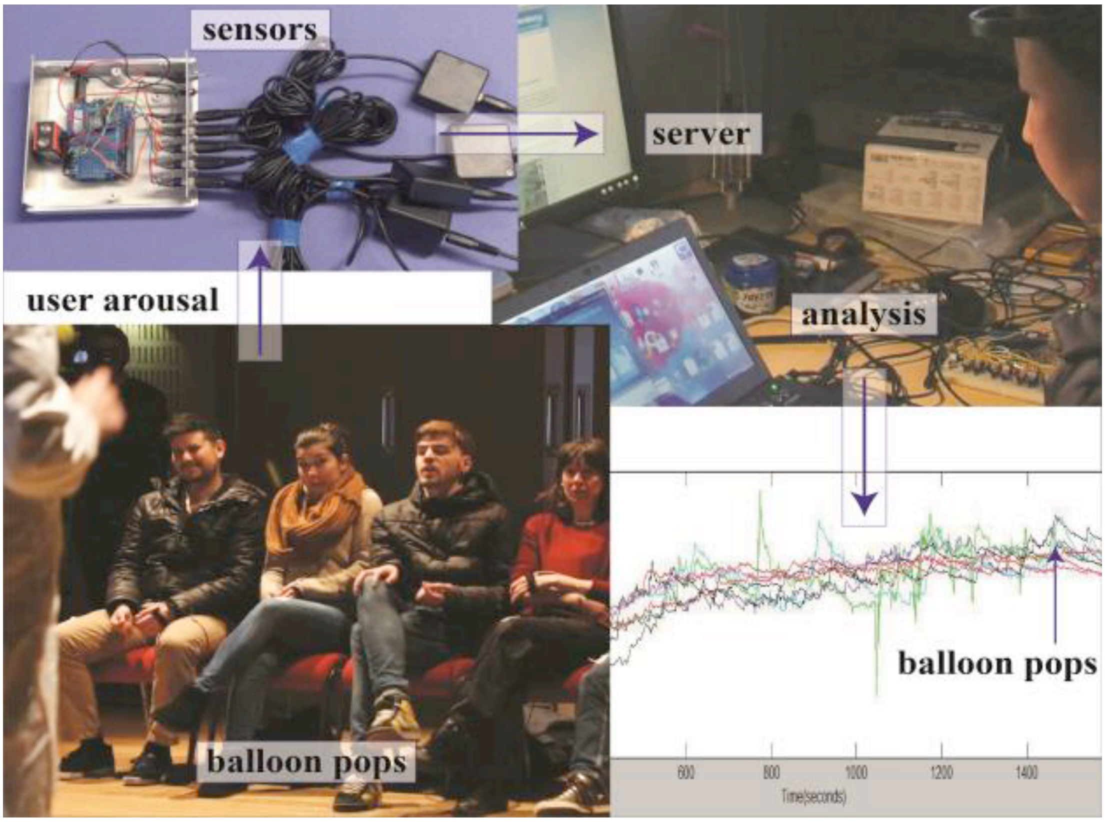


Figure 3.1: Wang et al.'s experiment measuring GSR in a live audience

Apart from GSR measurements, Vicary et al. (2017) and Devlin et al. (2017) both used a wearable device to measure heart rate variability in an audience when watching a live performance. Devlin et al.'s focus was more to test whether there is any synchronisation of the signals among the audience members while Vicary et al.'s research was focused more on the interactions of audience and performers.

Finally, research by Reason et al. (2016), Calvo-Merino et al. (2005) and Calvo-Merino et al. (2008) used functional brain imaging (fMRI) technologies to measure the neural signals of participants during recorded dance performances. However, given that current brain imaging technologies have form factors unsuitable for use outside the lab they are considered inappropriate for this research.

The methods described above measure audience responses that are implicit and not detectable by the performers. As mentioned above, the main focus of this research is to reveal the audience responses that performers could potentially sense, hence the covert audience responses described in this section cannot be used for the scope of this research.

### 3.4.2 Behavioural metrics - Audience overt responses

For moment-to-moment behavioural audience metrics, existing research suggests two different methodological approaches: in the first approach audience responses are collected using continuous self-report devices while the second approach follows a more naturalistic line measuring audience physical responses using video based methods or wearable devices.

Self-report devices have been extensively used in market research to find patterns of affective responses in advertisement. Some examples include the "warmth monitor" (Stayman and Aaker, 1993) and the "on screen cursor"(Baumgartner et al., 1997). These self-report tools share some of the limitations of a survey based methodology described in section 3.2 as they are verbally-mediated and might not necessarily be voluntary or conscious.

An example of such a device for live performances is the portable Audience Response Facility (pARF) (Stevens et al., 2007). The pARF is a PDA that is able to record audience responses during a work of dance. It consists of two different interfaces. The first one is able to measure engagement with a scale ranged from 0 - 10, where 0 refers to completely disengaged, and 10 to very engaged. The second interface measures moments of valence and arousal with the x-axis representing the valence (positive-negative) scale of emotion and the y-axis the arousal (aroused-sleepy) scale of emotion (see image 3.2).


Figure 3.2: Stevens et al.'s pARF tool

This technique does have the advantage of continuous data collection, but the engagement levels reported are the self-identified ones that might not be the same to those naturally felt. In addition, it is very likely that during moments of high engagement, audience members will forget to log how engaged they are on the PDA device. This was shown in a user experience survey about the interface (Stevens et al., 2014), where participants were distracted enough to not continuously report their engagement levels during a performance.

An example of the second approach that uses more naturalistic methods of looking at the audience, was a video-ethnographic methodology to explore audience dynamics in street performers in Covent Garden proposed by Gardair et al. (2011). The video recordings of these street shows were analysed using a video annotation software to capture the natural fine grain interactions that occur between the performers and the audience. However, while this method can offer rich data with high accuracy and detail, it can be very time consuming.

A more automatic method of sensing the audience has been used by Stevens et al. (2009) without tethering them to any hand-held device or survey. The authors' method used computer vision techniques to firstly track the eye movements of novice and expert observers as they watched the performance in a laboratory. According to Stevens et al. (2009) eye movements provided detailed, quantitative information about continuous visual attention and engagement. Stevens et al. (2009) used an EyeLinkII video-based pupil monitoring system to record eye movements from eight observers as they watched a five-minute dance film. Both studies happened under sufficiently good lighting conditions (natural daylight or indoor light) which does not commonly exist in real theatrical or dance performance settings. Thus, while eye tracking might be a good approach to allow for exploring visual attention, there is still no technology available that can be applied to the settings which are the focus of this thesis.

Questions relevant to audience engagement and to the live feedback that occurs between the performers and the audience have been addressed by Healey et al. (2009); Harris (2017); Katevas et al. (2015). They used motion capture techniques to explore the naturalistic generated patterns of head and body movement between performers and multiple audience members during a seminar and a stand up comedy. Such techniques can provide a lot of detail but need specialised equipment that is difficult to install in a theatre but also specialised suits that the audience need to wear.

More in line with the present research are the methods used by Katevas et al. (2015); Harris (2017); Vicary et al. (2017). Katevas et al. (2015) examined the effects of a humanoid robot programmed to perform a stand-up comedy routine to a live audience. To obtain fine-grained real-time response measures and automatic measures of facial display and position, Katevas et al. used sentiment analysis techniques developed in computer vision research. Finally, Harris (2017) and Vicary et al. (2017) both used wearable devices to measure laughter (breathing belts) and acceleration (wristbands) of audience members during a stand-up comedy and a dance performance respectively.

## 3.5 Description of methods used

While the previous two sections focus on existing methodologies that have been used to measure audience continuous responses, in this section the methodological approach followed in this research is presented. As mentioned above one of the priorities of this thesis was to collect continuous, overt audience data from real theatrical settings. For this, three studies were conducted that took place in three theatres in the UK. The methods used in each study differ among each other, with each study using a methodological approach that was based on the findings of the previous study. The research was started with an exploratory approach in the first study and finished with a more focused methodology that was testing specific hypotheses in the second and the third study.

Overall, the methods used can be divided in two broad categories: The first one includes a video based data collection approach using both a manual and an automatic method for the data extraction, while in the second one a more automatic and easy way to collect the data using wearable devices was used. Both methods were supported with a few pre and post performance questionnaires. The studies are presented in the following section with brief summaries and in more detail in the following chapters (Chapter 4,5 and 6).

### 3.5.1 Audience and dancers data collection

As mentioned above, audience overt responses include all the responses that are visible to the human eye. These responses might include the facial expressions or body posture of the audience members but most importantly how much movement occurs in the auditorium during the performance. The increase or decrease of movement is something that the dancers might be able to detect and it is thus a central focus of this thesis. To actually allow for testing for any possible influences between audiences and dancers, movement on stage was also recorded and analysed.

The core tool used in this thesis was video recording which also acted as the principal source for data analysis. Unlike more conventional ethnographic data, video recordings of the audience and the dancers can offer rich information about the live experience of the performance. Using manual annotation software or analysis techniques from computer vision research, video recordings can offer datasets that include audience facial expressions and hand gestures but also the amount of movement that occurs on the stage and the auditorium. Such techniques have been used extensively for automatic fine-grained extraction of features of human movements from video (Jakubowski et al., 2017).

Researchers have recently begun to test the efficacy of computer vision techniques for capturing and indexing human body movements during social motor coordination tasks Romero et al. (2017) and dance Sellent, A, Kondermann, D, Simon, S, Baker, S, Dedeoglu, G, Erdler, O, Parsonagr, P, Unger, C, Niehsesn, W (2012). According to (Romero et al., 2017) computer vision methods, as applied to video recordings, can perform similar tracking of body movements to more expensive techniques, such as Motion Capture(MoCap) systems or Microsoft Kinect under certain conditions. However, computer vision methods for motion tracking have been shown to be more feasible for tracking large-scale, full-body movements than movements of individual body parts Romero et al. (2017) and only measure movements in two dimensions (contrary to MoCap and sensors such as accelerometers, which measure movements in three dimensions).

In parallel to measuring the general movement in the auditorium and on stage, manual annotations tools such as ELAN were used (see section 4.3.2 in Chapter 4) to encode the hand gestures of the audience members. ELAN can be used to extract fine grained details of the footage and allows the footage to be manipulated in ways that enhance intelligibility, for example the ability to slow the footage down. However, while manual annotation can offer a very rich and accurate dataset for analysis it cannot give us continuous movement metrics and it can also be very time consuming for annotating long video recordings like the ones used in this research.

In order to extract the continuous hand movement of each audience member two different methods were used. In the first method a combination of computer vision and low-fi wearables (reflective wristbands) was used so as to isolate the hands from the rest of the body (more details on this in chapter 5, section 5.3.2). In the second method we used wearable devices with embedded accelerometers to measure acceleration of the hands of each audience member. Accelerometers have the advantage that any data they record can be extracted immediately without any processing as opposed to the computer vision analysis described above. However, due to the high price of each device the sample size had to be reduced.

Finally, pre and post performance surveys were used both as a supplementary information but also as tool to validate the continuous audience responses. Surveys were not used as a primary data collection method in this research but more as supplementary material to cross validate some of the results derived from the continuous data.

## 3.6 Time Series Analyses: Analysing continuous responses

For the analysis of the data, a three-tier approach was used that combined continuous measures of movement, frequency and discrete measures of hand gesture as well as self-reporting data sources. A variety of analysis methods were used throughout this thesis, an introduction of which is reported below.

### 3.6.1 Granger Causality analysis

When working with time series, one important thing we usually want to test is whether one series “causes” changes in another. In this research in particular, relationships between audience and dancers responses were examined as well as between audience responses and other aesthetic elements of the performance such as the volume of the soundtrack and the video projection of the dance perfomance.

Numerous methods exist for identifying similarities between pairs of time series. These include dynamic time warping, spectral coherence, ARIMA modelling, correlation and granger causality (GC) analyses. Based on the work of Vicary et al. (2017) and

Howlin et al. (2017) on audience responses during dance performances, GC analysis was considered the most appropriate method for the time series analysis in this study.

In contrast to cross correlation, GC accounts for presence of autocorrelations and is able to identify meaningful lagged relationships between two time-series at different timescales. A predictor variable, x, is said to "granger cause" a response variable y, if information about the previous values of x is useful in predicting future values of y, over and above prediction based on information about previous values of y alone Granger (1969).

Time series derived from human behavioural and physiological data such as heartrate, skin conductance (GSR), continuous perceptual responses or movement often exhibit autocorrelation (Dean and Dunsmuir, 2016). When a time series is autocorrelated, this means that the current value of the series parameter is dependent on preceding values, and can be predicted (at least in part) on the basis of knowledge of those values (Dean and Dunsmuir, 2016). It is important to realise that if two quite independent time series datasets are each highly autocorrelated, they may well seem to be significantly cross-correlated. Thus to avoid identifying spurious relationships between series it is necessary to create "stationarity" (Dean and Bailes, 2010). To ensure stationarity, all timeseries of continuous data in this thesis were differenced by subtracting consecutive sample points from each other prior to applying GC (more information is provided in the section Audience-Dancers interaction in each of the following chapters).

In addition, a relationship between audience and dancers movement is considered predictive only if it is unidirectional (Vicary et al., 2017). If the GC results show a bidirectional relationship between the two variables we assume that there is an exogenous variable that affects both audiences and dancers. According to Dean and Dunsmuir (2016) exogenous variables can be considered to be all the elements of the performance that cannot be influenced by the audience such as the soundtrack or any visual projections that are included in the performance.

Finally, existing research suggests that there are several ways to identify the appropriate lag structure for the GS analysis. One way is to choose among a wide variety of model selection criteria. However, according to Batten and Thornton (1984) different selected statistical criteria for determining the lag structure might show contradictory conclusions on the GC results while it appears that the safest approach is to perform an extensive search of the lag space. Based on this, we chose the lag order based on the frequency of the data. Since in all the three studies the frequency of the data was 1Hz, we decided to use as a starting point the lag order of 1 and test GS for lags twice the frequency. This is also supported by the research of Muth et al. (2015) and Vicary et al. (2017) that argues that the aesthetic responses to dynamic art forms such as dance and music are likely to involve a sampling period of at least a couple of seconds.

In this thesis, Granger Causality analyses are made and illustrated with R, an open-source language and environment for statistical computing (R development core team, 2007), freely available at http://cran.r-project.org. The R package "lmtest" (Zeileis and Hothorn, 2002) incorporates the GC procedure using a Wald test that compares the unrestricted model— in which y is explained by the lags (up to the defined order) of y and x—and the restricted model—in which y is only explained by the lags of y.

GC is applied on each of the three studies separately (Chapters 4,5 and 6) and a detailed discussion on the results is provided in Chapter 7.

### 3.6.2 Generalised Linear mixed models

Standard statistical analysis methods, such as analysis of variance (ANOVA) and multiple regression do not take into account repeated measurements from the same statistical units which is a characteristic in most of the datasets of this thesis. In addition, linear regression analyses can deal with large data sets but do not allow the construction of a model that specifies interactions between the fixed and random effects.

To address this, several Generalised Linear Mixed Model (GLMM) analyses were performed on the collected aggregated datasets to analyse relationships between audience responses in different parts of the performance, differences in their hand behaviour as well as to compare survey responses with aggregated time series data. For each case the distribution that was appropriate to the data was used.

Numerous studies have adopted GLMMs for the analysis of continuous and subjective human measurements (Solberg et al.; Katevas et al., 2015). GLMMs estimate the relationship between a dependent variable and associated covariates by taking into account both fixed and random effects. They also allow for missing data points for subjects, which was the case with some of the data-sets in this study. They are used to model the combined random effects, categorical and interval fixed effects and repeated measures involved in the audience responses obtained.

In this thesis, we illustrate mixed-effects modelling with R using the lme4 package (Bates et al., 2015; Bates, 2007) that offers fast and reliable algorithms for parameter estimation. However, the lme4 package provides many ways for evaluating the significance of fixed effects of the GLMM (Luke, 2017). The reason for this is that in linear mixed models applied in an unbalanced dataset it is not obvious what the appropriate denominator degrees of freedom to use are. In this thesis a likelihood ratio test (LRT) was used to compare two different models to determine if one is a better fit to the data than the other. In a GLMM, LRTs are used to decide if a particular fixed or random effect should be retained in the model by evaluating whether that effect improves the fit of the model. According to Luke (2017) among other methods LRT is one of the most common methods used for evaluating significance.

## 3.7 Summary

Overall, this chapter presented some example studies that explore audience behavioural responses during live events. Most of these studies explore audiences in non-naturalistic environments or using post-performance methods while only a few of them manage to record audience responses using both a naturalistic method and a satisfied sample size. As a result, many basic questions about audience engagement, the dynamics of collective and individual responses during a live event and the ways in which these responses are captured and transmitted remain unanswered. In addition a summary of the methods used for data collection is presented as well as a brief description of the statistical analysis techniques we followed to analyse the data. In the following chapters, we show how this methodological approach was adopted to study the audience and dancers responses in three empirical studies (Chapter 4, 5, and 6). Chapter 7 provides a detailed assessment and discussion of the results of those three studies.

# Chapter 4

# Audience responses part I: Recognising audience overt responses

## 4.1 Introduction

This chapter presents the first exploratory study of this thesis, which was designed to investigate the behavioural responses of a live audience during a contemporary dance performance. Exploratory studies provide means of revealing previously unimagined connections and causal mechanisms; and are well suited to cases where little is known about the area of interest (Reiter, 2013).

The study took place at the Theatre Royal in Glasgow, where the contemporary dance performance "Frames" made its world premier. "Frames" was one of the three dance performances that the Rambert Company presented in Glasgow, over a period of 3 days, on the $5^{th}$, $6^{th}$ and $7^{th}$ of March 2015. Informed by the methods and techniques discussed in the previous chapter, continuous quantitative measures were extracted from recordings of the audiences and the dancers during the three days of the performances. In this chapter, the data collected during the first performance, on the $5^{th}$ of March was analysed. A detailed description of the methodological approach, as well as a broad analysis of the data are undertaken here, and the findings are reported below.

## 4.2 "Frames" - A contemporary dance performance by Alexander Whitley

"Frames" (see figure 4.1) is a contemporary dance performance that presents the Rambert dance company in a choreography directed by Alexander Whitley in collaboration with the artists Revital Cohen and Tuur Van Balen and with music made by the composer Daniel Bjarnason. It is 37 minutes in duration and has a cast of 12 dancers. The piece incorporates movement, visual setting elements (lighting, set-design etc) and aural elements (live music). The concept of the piece is broadly related to the notion of production, focusing on the manufacturing of objects as well as the manufacturing of experiences in the context of the theatre and how people - in this case dancers - can organise such processes (Whitley, 2015). "Frames" explores these ideas by using the theatre as a microcosm for these processes to unfold. In his interview at the DanceTabs magazine Whitley said

> "I've been interested for a long time in the connection between choreography and industrial manufacturing in terms of how people's movements are coordinated and synchronised, and to a large extent habituated by repetitive processes. I was fascinated to learn, for example, that Rudolf Laban worked with industrialists in the mid-20$^{th}$ Century to try and improve efficiency in factories by applying his principles of movement from dance" (DanceTabs, 2015).

On stage, dancers construct different shapes using metal structures (frames) and portable light objects. As the choreography and the metal structures emerge, different images come to life that create a stage within a stage.

The performance begins with a short section in which one of the dancers organises the stage by placing the metal structures and the light objects in various locations to be ready for the dancers to pick them up during the performance. For the sake of the data analysis, this section will be called "pre-performance". The performance starts with a solo accompanied by music. At the end of the solo, the other 11 dancers come on stage and with some choreographed movements start to arrange the metal frames around the stage. During the performance, the dancers use the frames to build up different shapes controlling them with their bodies and in collaboration with the other dancers. The performance ends with the frames hanging from the ceiling and the dancers performing a final choreography accompanied by intense music.

"Frames" had its world premiere at the Theatre Royal Glasgow on the 5$^{th}$ of March 2015, followed by presentations in Inverness and Brighton, with a final performance at Sadler's Wells in London.

The Theatre Royal (see figure 4.2) is the oldest theatre in Glasgow, it opened in 1867, and it is considered the home of the Scottish opera and ballet. Today, it is operated by the Ambassador Theatre Group. It has an old style architectural character with a big stage and can accommodate up to 3000 people.

Figure 4.1: "Frames", a contemporary dance performance directed by Alexander Whitley

## 4.3 Materials and Methods

### 4.3.1 Data capture: Equipment and technical specifications

"Frames" was recorded during the three days that the performances were taking place. For the filming of the audience, a Basler ace camera (1280x1024px resolution) was used and the relevant Basler Pylon software operated on a Windows 7 PC. In order to be able to film the audiences during the dark periods of the performance, two infrared lights (IR) were used, directed at the part of the audience being filmed. The camera and one IR light were placed in the right front box (small separated seating area) both angled at a sample of audience seated in the first circle while the second IR light was placed in the left front box pointing again in the right direction (see diagram in figure 4.9 below). Two lenses were available within the camera box, one with 16 (23.99$^\circ$ angle) and one with 25 (15.49$^\circ$ angle) focal length. In order to achieve the maximum possible resolution for each person, the 16 focal length lens was used. The performance was filmed by the choreographer and the video recording was given to us a few days after the performance.

Privacy was also an issue in this study since the aim was to extract personal but anonymised data from the audience members. The study was certified with an ethical approval from the Ethics Committee of Queen Mary University of London (Ethical approval reference number: QMERC1432a) and a sign was placed in the foyer of the theatre to inform audience members that filming was taking place during the performances for research purposes (see appendix A for the Ethical Approval).

The sign at the foyer read as follows:

> "IMPORTANT NOTICE: During the performance we will be filming the audience for research purposes. Audience members who do not want their image to be used in the film please contact me at: l.theodorou@qmul.ac.uk"

Figure 4.2: The Theatre Royal in Glasgow

### 4.3.2 Continuous Dataset: Audience and dancers

Following several observations of the video footage that was collected during the performance, the analysis was focused on the extraction of audience and dancers average velocity as well as audience hand-to-face gestures and facial expressions. The data processing pipeline (see figure 4.9) consisted of: 1.Optical flow algorithm made by Greg Borenstein, this was used to calculate the movement of the audience members and the dancers. 2.ELAN, a professional tool for the creation of complex annotations on video resources, was used to code the hand-to-face gestures of each individual audience member and 3. SHORE$^{TM}$ a facial analysis software made by Fraunhofer Institute for Integrated Circuits, this was used to extract all the facial features of each audience member during the performance (Küblbeck and Ernst, 2006).

**Visual edits**

VirtualDub software was used to read the video recording of the audience and down-sample the data from 45fps to 29.97fps in order to synchronise it with the dancers recording. Following this, ELAN was used to synchronise the video of the audience with the video of the performance. There was an issue with synchronisation since the Basler Pylon software did not provide a timestamp and the accuracy of the synchronisation was not very good. This happened mainly because during the filming the software did not capture with a stable framerate but also because Processing was not able to read the video and export the data frame-by-frame.

**Average velocity of audience and dancers**

Average velocity in dancers and audience video recordings was measured using the optical flow algorithm. Optical flow estimates frame-to-frame motion by measuring the flow of grey values on the image plane. Under reasonable assumptions, this approximates the projection of the actual motion field in the 3D scene over the camera plane (Jähne, 1997). In optical flow, characteristics such as edges or angles are identified within each section of the video frame. In the next frame, such characteristics are sought again. A speed is then associated to each pixel in the frame; the movement is determined by the ratio between the distance in pixels of the displacement of the characteristic in question and the time between one frame and another.

A number of optical flow algorithms are available in the literature. The version of optical flow that was implemented in this research is known as dense optical flow, is well suited to the challenging illumination conditions of this study and is based on the algorithm presented in (Farnebäck, 2003). In particular, we relied on the OpenCV for Processing implementation made available by Borenstein (Borenstein, 2013). For the purposes of the study, the integral of the magnitude of the flow field across the entire frames of audiences' and dancers' videos was calculated. This represents an estimate of the average level of motion; high values result from either fast motion in one area of the video or distributed motion across the video, irrespective of the direction of motion and of its coherence. In the rest of this thesis, this will be referred to as the "average velocity". Figure 4.3 shows an example of optical flow calculation.

It should be noted that the algorithm used has also some limitations. In particular, one common assumption used in most optical flow algorithms is the brightness constancy assumption. This assumption states that the grey value of corresponding pixels in the two consecutive frames should be the same. Unfortunately, in the case of an indoor performance similar to the one studied here, there are frequent light changes, shadows and glossy surfaces that may degrade the results of apparent motion that is happening on stage as well as on the stalls. Since the analysis is focused more on the relative changes in the movement at each time interval, absolute illumination would not therefore significantly affect the results.

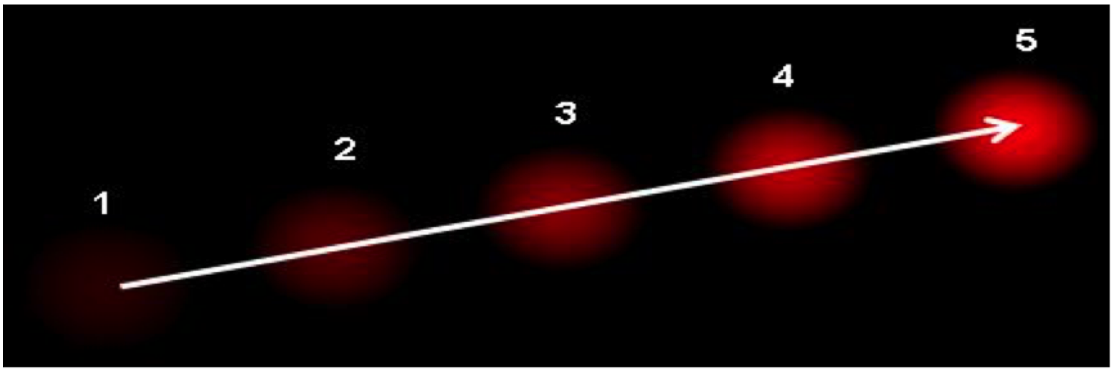


Figure 4.3: Example of optical flow calculating the movement of a circle

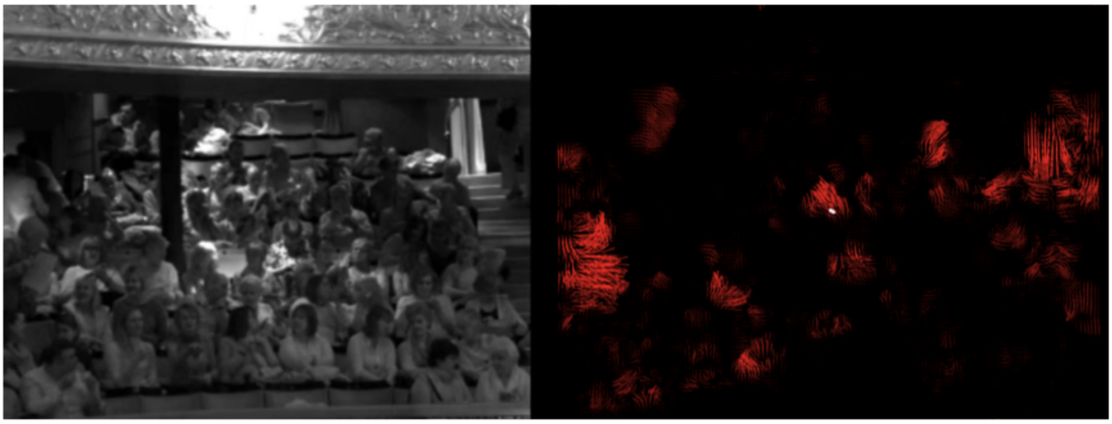

Figure 4.4: Optical flow algorithm running on the video of the audience

Figure 4.5: Optical flow algorithm running on the performance video

**Audience hand to face gestures**

In this study ELAN was used to extract data for different types of hand-to-face gestures performed by each audience member during the performance. ELAN is a software used for qualitative video analysis, to record social activities and the use of tools, objects and artefacts in real time. It is able to focus on detail through controlled, repeated frame-by-frame analysis. It allows video footage to be mounted within an annotation frame, facilitating iterative addition of annotation layers. The footage can be slowed down or stepped through frame-by-frame and multiple video sources can be analysed synchronously. Layers to describe both gestures and dialogue can then be developed which are then used to accurately map the precise timing of actions and attribute them to each participant. Following the coding of the video, the data can be exported to a comma separated values (csv) file that is ready for further analysis. Using this method, a detailed picture can be built up to show how participants interact and behave during the performance (see a screenshot of ELAN interface in figure 4.6).

The coding structure was organised as follows. Hand gesture activity was separated into different hand behaviour tiers for each participant. General hand gestures tiers were created in the first round of coding, for example "Hands up". In the second round, specific behaviours of the hands (such as "Hands scratching", "Hands drinking", "Hands fixing hair" and "Communicative hand gestures") were coded while in the final round of coding different tiers for the right and the left hand (e.g "Left hand drinking", "Right hand scratching") were added. ELAN automatically records the start time and duration of each hand to face gesture and is able to export this as a csv file. Since the above hand gestures are considered as simple physical movements that is very unlikely to be ambiguous, inter-judge coding was not considered necessary.

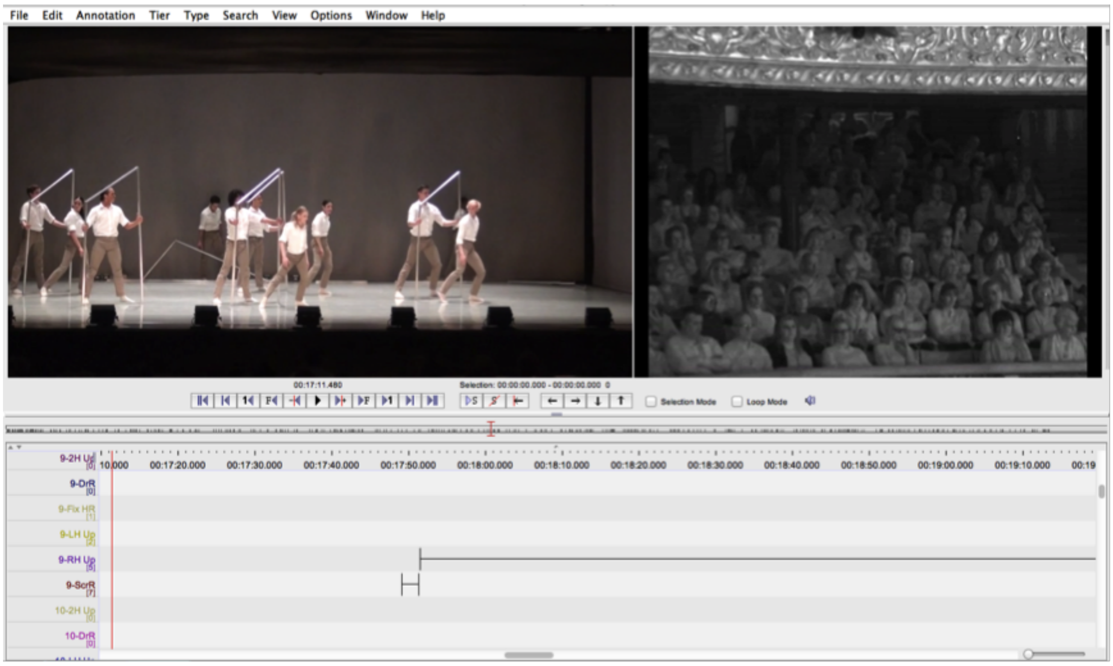


Figure 4.6: Screenshot of an analysis section from ELAN software

A description of all hand to face gestures coded for each participant is presented below. These 10 categories of gestures were represented as tiers in ELAN:

Table 4.1: Hand-to-face gesture categorisation

| | |
|---|---|
| Two hands up | Both hands of the participant are supporting the head. |
| Left hand up | The left hand of the participant is positioned on his/her face. |
| Right hand up | The right hand of the participant is positioned on his/her face. |
| Left hand drinking | The participant is drinking using his/her left hand. |
| Right hand drinking | The participant is drinking using his/her right hand. |
| Left hand scratching | The participant is scratching his/her face with the left hand. |
| Right hand scratching | The participant is scratching his/her face with the right hand. |
| Left hand fixing hair | The participant is fixing his/her hair with the left hand. |
| Right hand fixing hair | The participant is fixing his/her hair with the left hand. |
| Communicative hand gestures | The participant is waving his/her hand or both hands while talking. |

To simplify the data analysis, the above categories are grouped in the three "super-ordinate" categories. The three first categories from the table above (below: Two hands up, Left hand up, Right hand up) were grouped in a singe category named "Hands still on face" while the rest of the tiers (Left/Right hand drinking, Left/Right hand scratching, Left/Right hand fixing hair, communicative hand gestures) were grouped in a second category named "Hands moving on face". Finally, the category "Hands down" was created to represent the period where there is no hand to face gestures. This category was considered as the time that participants do not perform any of the hand gestures described above although other hand movements not caught by the camera might have occurred when the hands were down.

Figure 4.7: Example of line drawings of some of the hand gestures coded in ELAN

In order to be able to examine the behaviour of hands continuously throughout the performance, the discrete dataset exported from ELAN was converted to a continuous using a script written in Processing. The continuous dataset contains the frequency of each hand behaviour for every second of the performance.

**Audience facial expressions**

A computer vision framework, SHORE$^{TM}$ (Sophisticated High-speed Object Recognition Engine) (Küblbeck and Ernst, 2006) was used to extract continuous measures of the degree of happiness, sadness, surprise and anger for each audience member described as percentages. SHORE$^{TM}$ is a cross-platform computer vision framework designed by the Fraunhofer Institute for Integrated Circuits for detecting, analysing and identifying faces from video streams. Even though all internal parts of the framework are hidden, it can be configured or even extended using the LUA Scripting language.

The properties that SHORE$^{TM}$ can extract for every identified face, as listed in the official website of Fraunhofer IIS, are the following:

1. Location of the face in the space
2. Position of the eyes, nose and mouth
3. Gender classification ('Male', 'Female' or 'Unknown')
4. Age estimation in years
5. Facial expression recognition, described as percentages of 'Happy', 'Sad', 'Angry' and 'Surprised'
6. Identify whether the eyes are open or closed
7. Identify how much the mouth is open
8. Detection of up to $60^\circ$ of face rotation

Most of the above features have been validated using external data sets. The face detection has been validated using the CMU+MIT datasets and showed good accuracy relative to other classification methods (91.5% detection rate with a 1 in 10 miss rate). The gender classification has been validated using the BioID dataset (94.3% recognition rate) as well as the Feret fafb data set (92.4% recognition rate). Finally, the happiness analyser has been validated on the JAFFE database (95.3% recognition rate). Note that none of these test datasets were used as training sets for the framework. Further information can be found on the Fraunhofer IIS website: http://iis.fraunhofer.de.

For accurate tracking SHORE$^{TM}$ requires a minimum face size in the image of 35x35px. This requirement was satisfied in the captured video. However, it should be noted that these estimates are not always reliable as that there are short video segments in which the software was not able to detect enough faces due to the rotation of the head or people placing their hands on their face. Nonetheless, based on other researchers (Katevas et al., 2015) that used the software in similar conditions the measure appears to be robust over extended periods.

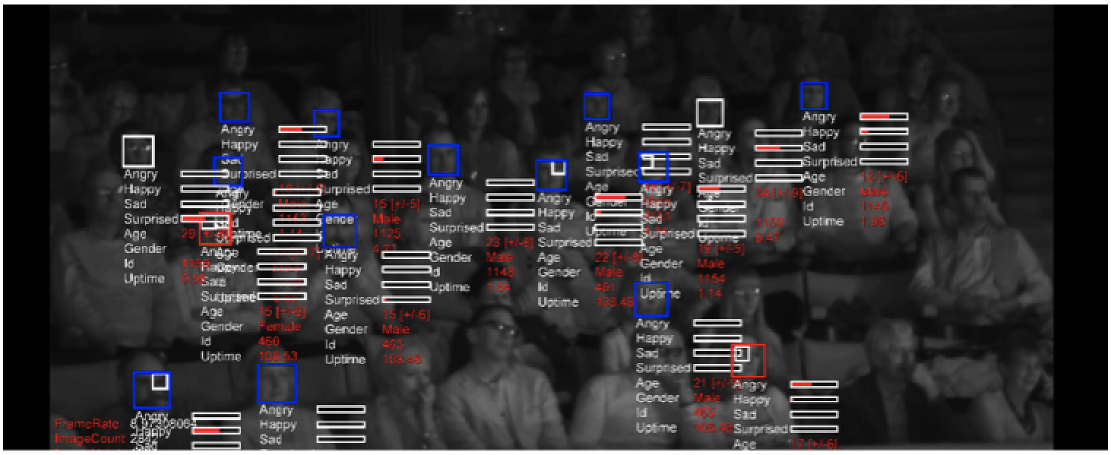

Figure 4.8: SHORE$^{TM}$ software running on audiences' footage during the second day of "Frames"

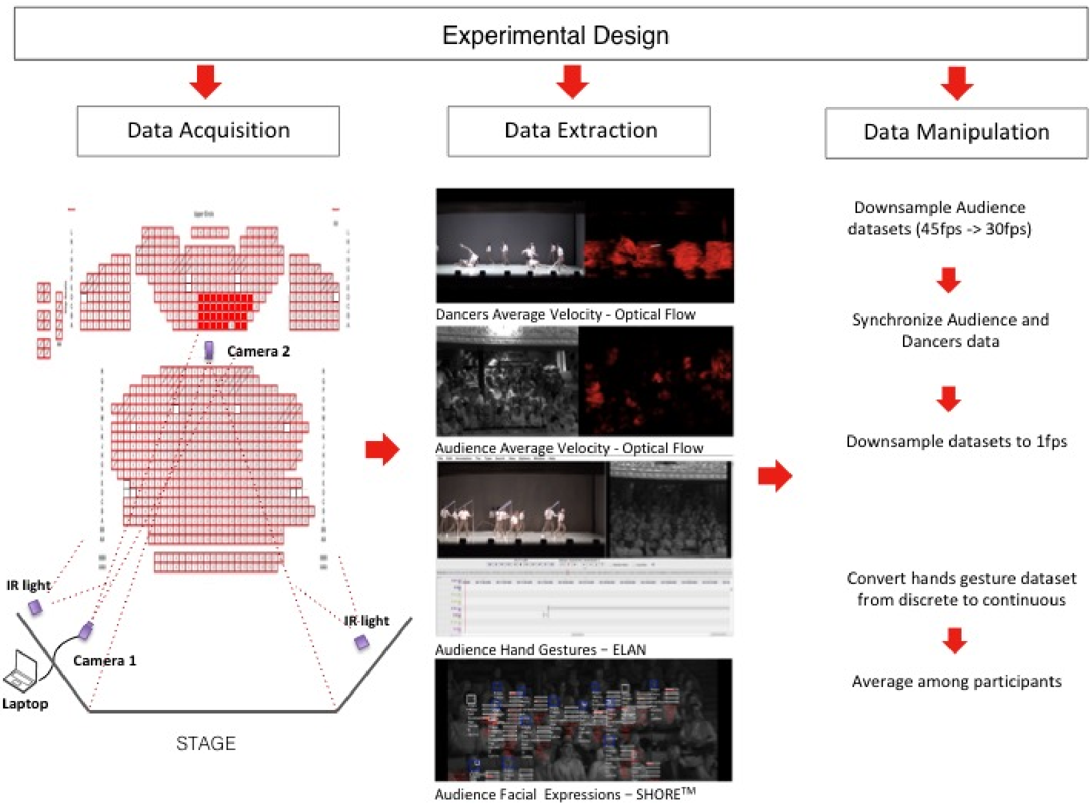


Figure 4.9: Study I: Data collection and data processing pipeline

**Data preprocessing**

The camera captured a section of 53 audience members. However, the sample size of each dataset is different depending on the method used to export or code the data (see section 4.4 for more details). In total, two datasets were generated. The first one consists of seven timeseries data. One was extracted from the performers and includes the average velocity calculated using optical flow algorithm. Six time-series variables were derived by averaging the spectators following datasets: 1. facial expressions (displayed anger and happiness) and 2. the frequency of the three hand gestures (Still on Face, Moving of face, Communicative hand gestures). It was decided that a sampling rate of 1Hz for the compiled data set was appropriate given earlier studies (Schubert, 2004), which indicate that in similar circumstances real-time perceptual responses generally take at least 1 to 5 seconds for full registration.

### 4.3.3 Interview with Alexander Whitley

For a better understanding of the choreographic structure and narrative of the dance piece, the study was supported by a semi-structured interview with the choreographer Alexander Whitley. The main aim of the interview was to acquire information about the structure of the performance "Frames" and identify any specific moments of the piece that according to Whitley might affect the audience.

The interview took place at Queen Mary University on the $15^{\text{th}}$ of June 2015. It was expected to last about 2 hours but due to its open-ended conversational style, it finally lasted around 3 hours and 30 minutes. The interview was semi-structured and conversational in style to avoid leading the interviewee in a particular direction and designed to move from the general idea of the piece to the discussion of specific moments. The interview was tape-recorded both from a laptop and from a zoom recorder.

The first part of the interview focused on the initial idea and the general concept of the performance. Whitley was asked to describe the main idea behind the performance “Frames”, how he first came up with the idea and if it was an improvement or a continuation of a previous project. He was then asked to divide the performance into what he considered the most important parts. To do so we went through the video of the performance step by step and Whitley pointed out the important transitions of the piece. For each of these transitions, Whitley was asked what kind of expectations he had from the performance during these periods of time and if the expectations were similar to the ones he had from the audience. Finally, we asked him to point us to any periods during the performance that something unexpected happened or something that didn’t work well (The interview protocol can be found in Appendix A).

## 4.4 Results

This section presents the results of the first study that took place on the 5$^{th}$ of March 2015 at the Theatre Royal in Glasgow. The main aim of the study was to identify any significant responses in the behavioural reactions of the audience during the dance performance "Frames". The analysis was carried out based on the data collected during the first (audience hands and body responses) and the second (audience facial expressions) day of the performance. The results are reported in three parts. Firstly, the audience responses were examined separately for the facial expressions, hand to face gestures and continuous overall movement in the auditorium. Then, possible connections between the movement of the audience and the dancers were tested. Finally, an analysis of possible audience responses during moments of heightened dramaturgy identified by the choreographer Alexander Whitley was carried out.

Figure 4.10: Screenshot of the audience members during "Frames" on the 5$^{th}$ of March 2015

### 4.4.1 Audience facial expressions

Due to unexpected events that took place during the first day (5th of March) of filming, the fidelity of the video wasn't high enough for the SHORE$^{TM}$ facial analysis software to detect a sufficient number of faces. The two figures below represent SHORE$^{TM}$ software applied to the audiences' footage during the first and second day of the performance. It is clear that the software was able to detect more faces in the second day of the performance compared to the first.

For this reason, the results presented below belong derive from the video of the second day of the performance. The software was able to accurately track 17 out of 41 audience members. The same 17 people were tracked for the whole duration of the performance.

The measures of happiness, anger, surprise, and sadness produced by SHORE$^{TM}$ showed substantial inter-correlations. For example, happiness and anger levels are negatively correlated (r=-0.46, p<.001).

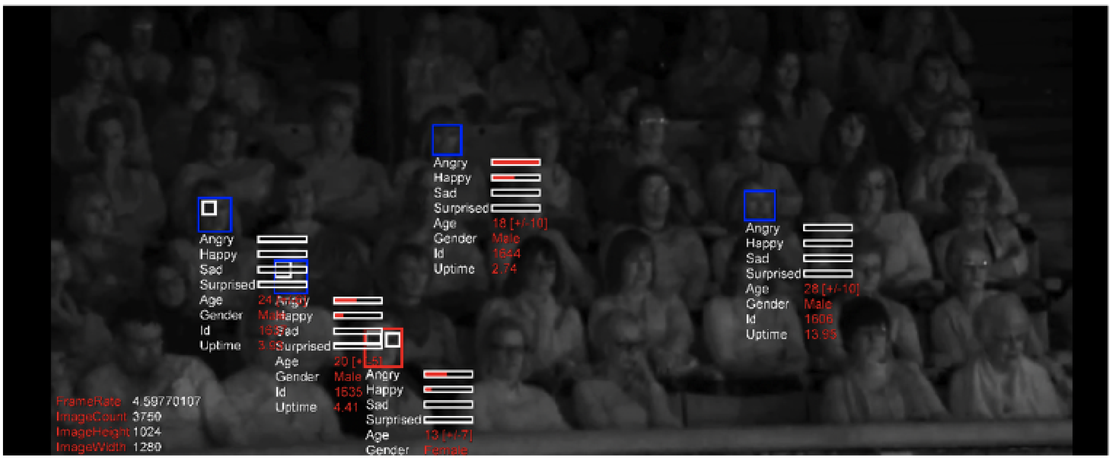


Figure 4.11: SHORE$^{TM}$ software running on audiences' footage during the first day of "Frames"

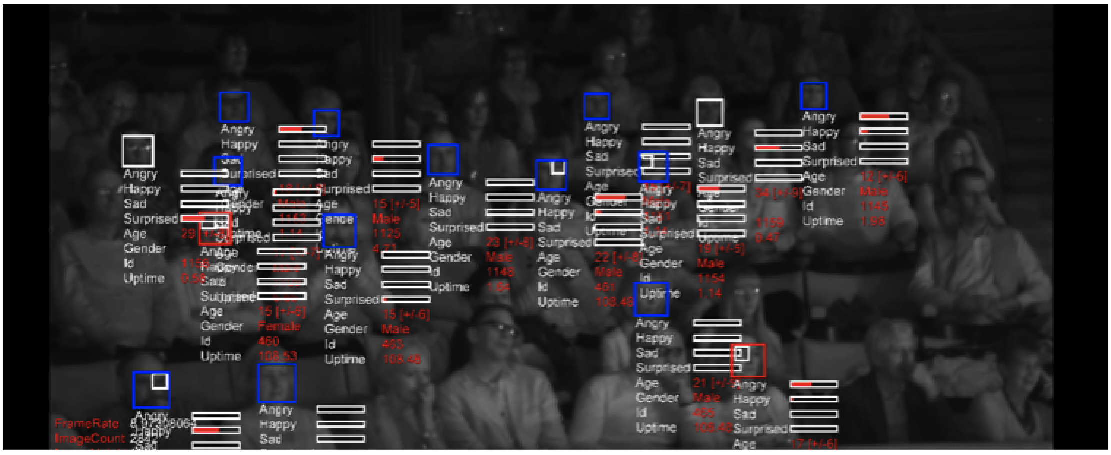

Figure 4.12: SHORE$^{TM}$ software running on audiences' footage during the second day of "Frames"

The two plots in figure 4.13 below show the average levels of displayed "happiness" and "anger" during the performance parts and during the non-performance parts. For the non-performance parts, data before the performance and data during the applause sections were added together. From the plots below, it is apparent that the displayed anger levels of the audience members increase during the performance parts and decrease during the non-performance while the opposite pattern exists for the displayed happiness data. To validate this, both the average happiness and anger levels displayed by the audience were analysed in a Generalised Linear Mixed Model (GLMM) using a Gamma distribution (see distribution fit in appendix A). For this performance state (Non-Performance or Performance) was defined as a fixed factor and audience member as a random factor. The model shows a main effect of performance part on audience displayed happiness (Chi-sq=13.876, $p < 0.01$) and on displayed anger (Chi-sq=4620.5, $p < 0.01$). The GLMM results are reported in tables 4.2 and 4.3 below.

Following several observations of the output of the SHORE$^{TM}$ software applied to the audience footage it became apparent that in this context the software tends to report anger when audiences have blank faces. This lack of expression of the audience members during the performance is an unexpected finding which is discussed further in the last section of this chapter.

Table 4.2: GLMM model for displayed "happiness" (performance vs non-performance)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| During performance (Happiness levels) | -0.03 | 0.01 | -3.73 |

Table 4.3: GLMM model for displayed "anger" (performance vs non-performance)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| During performance (Angrer levels) | 14.15 | 0.21 | 67.97 |

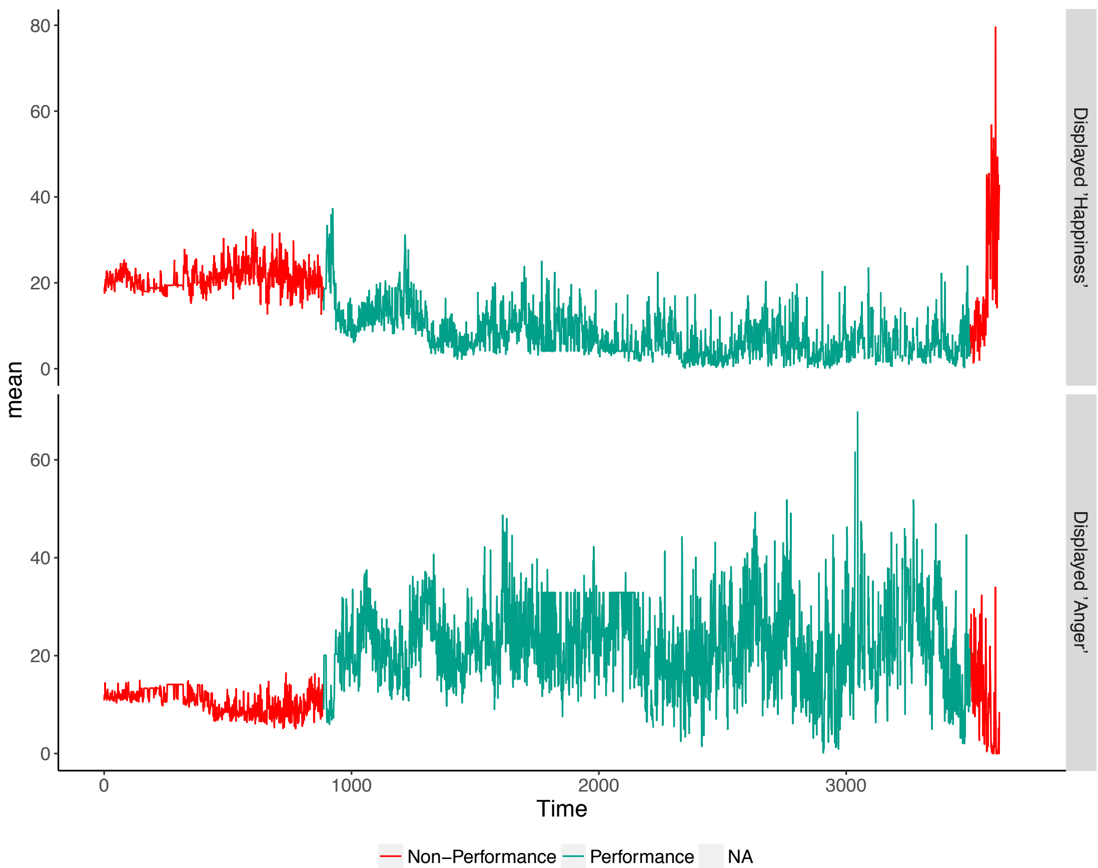


Figure 4.13: Average facial expressions of the audience members before, during and after the performance. Y-axis shows the average anger of happiness levels across the audience represented in percentages. X-axis shows the time in the performance in seconds

### 4.4.2 Audience hand to face gestures

Hand to face gestures were extracted from the ELAN software for 33 audience members (3 males, 30 females). Overall, it is apparent from the box-plot below (figure 4.14) that people keep their hands still on their faces about equal amounts of time compared to keeping their hands down (40 seconds on average) while the duration of hands moving on face is much shorter compared to hands down and hands still on face (4 seconds on average). To check if there are any statistically significant differences between the time people keep their hands moving on face and keep their hands still on face, the duration of each behaviour was analysed in a Generalised Linear Mixed Model (GLMM) with a gamma distribution (see distribution fit in appendices A). For this hand behaviour (hands moving on face, hands still on face) was defined as a fixed factor and audience member as a random factor. The results show a general effect of the hand activity on the duration that is performed (Chi-sq=472.39, $p<0.01$), with hands being still on face for longer periods of time compared to hands moving on face (see table 4.4).

Table 4.4: GLMM model for hand activity (Hands moving on face, hands still on face)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| Hands still on face | -0.31 | 0.01 | -21.73 |

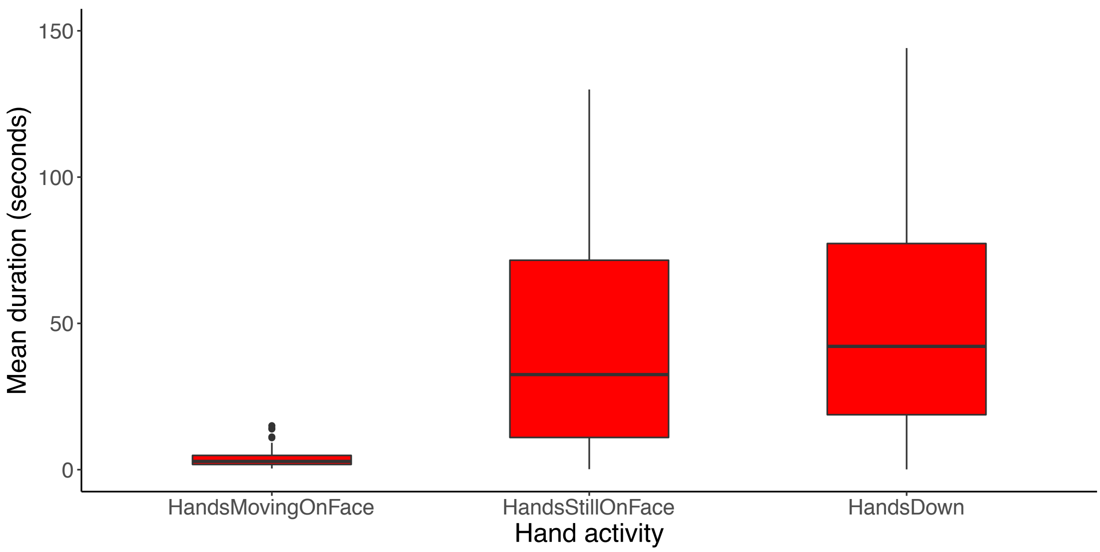


Figure 4.14: Box-plot of the median values of duration for three actions: a. Hands down b. Hands still on face c. Hands moving on face

In the two more detailed plots below (figures 4.15, 4.16), each hand activity is presented separately. The first plot (figure 4.15) shows the mean duration of each activity and the second plot (figure 4.16) shows the number of times each activity was performed during the performance.

To check for any statistically significant differences between the duration that people perform an activity using the right or the left hand, the duration of each activity was tested in a GLMM using a gamma distribution. Each activity was examined separately defining hand asymmetry (e.g right hand up versus left hand up) as a fixed factor and audience member as a random factor. Overall the results do not show any effect of hand asymmetry on the duration that each activity was performed. In particular, hand asymmetry has no effect on fixing hair (Chi-sq=0.123, p=0.72) and scratching (Chi-sq=0.20 , p= 0.65) activities as well as when hands are still on face (Chi-sq=1.32, p=0.24).

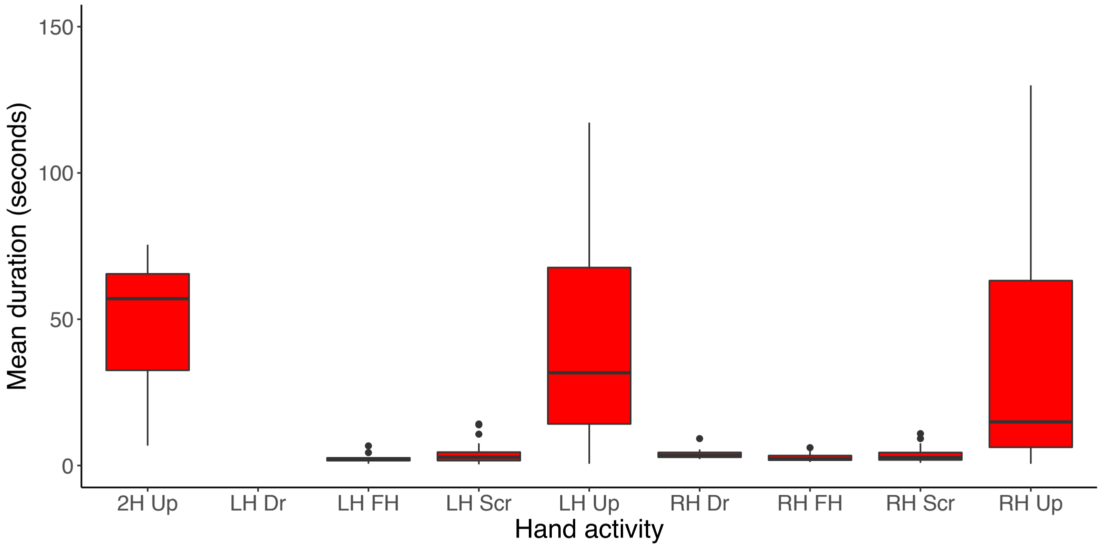

Figure 4.15: Box-plot of the median values of duration for the eight actions

Table 4.5: GLMM model for hand asymmetry (duration of right vs left hand being still on face)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| Right hand up (RH Up) | 0.00 | 0.00 | 1.15 |

Table 4.6: GLMM model for hand asymmetry (duration of right vs left hand fixing hair)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| Right hand fixing hair (RH FH) | -0.03 | 0.09 | -0.35 |

Table 4.7: GLMM model for hand asymmetry (duration of right and left hand scratching)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| Right hand scratching (RH Scr) | 0.01 | 0.02 | 0.45 |

Even though, the results show no significant difference between the left and right hand behaviour, the boxplot below shows that during the performance people keep their left hand up for longer compared to the right hand. This finding is supported by the results of the GLMM analysis (poisson distribution) applied on the frequency that each activity is performed during the performance. This was tested for each activity separately defining hand asymmetry as a fixed factor and time as a random factor. The results show a main effect of hand asymmetry on the frequency of hands being still on face (Chi-sq=1043.4, p$<$0.001) with the right hand being used less compared to the left. The results show no effect on scratching (Chi-sq=2.571, p=0.1) and fixing hair (Chi-sq=2.6351 , p=0.1) activities. An additional finding that is supported from both plots and from the GLMM analysis of frequency is that people used only their right hand for drinking (Chi-sq=3.7206, p=0.05) which is probably a reflection of hand asymmetry since we would expect right-handers to be more in the random sample.

Finally, figure 4.16 shows that the number of times people scratch their face (or head) during the performance is higher compared to the times that they perform the other gestures: 118 times people scratch their face with their left hand and 105 times with their right (223 times in total for the whole duration of the performance).

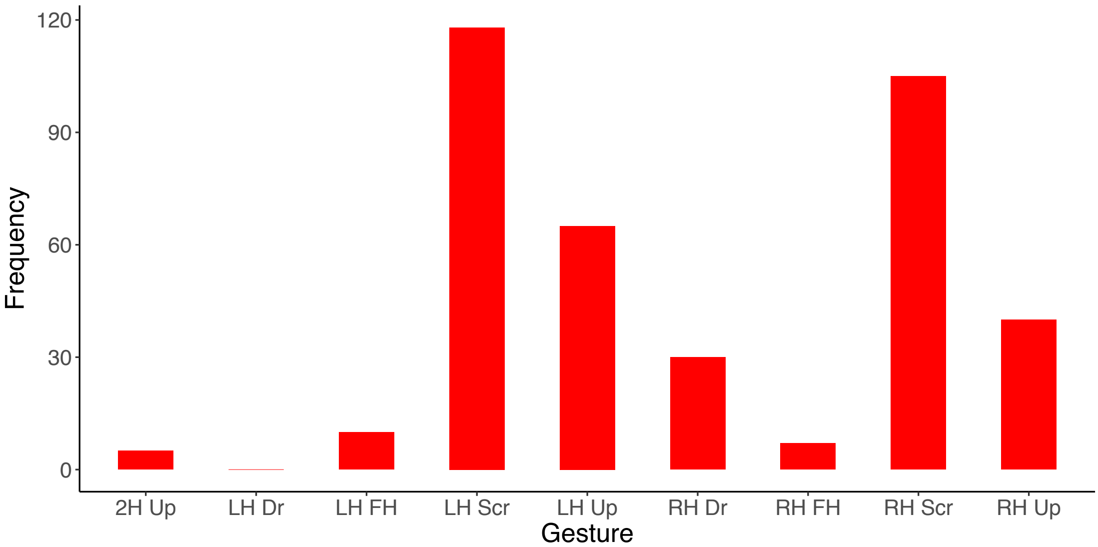


Figure 4.16: Total number of times people perform an action during the performance (This might include any activity performed by the same audience member at two different times)

Table 4.8: GLMM model for hand asymmetry (right vs left frequency of hands being still on the face)

| | Estimate | Std. Error | z value |
|---|---|---|---|
| Right hand up (RH Up) | -0.76 | 0.02 | -32.30 |

Table 4.9: GLMM model for hand asymmetry (right vs left frequency of hands fixing hair)

| | Estimate | Std. Error | z value |
|---|---|---|---|
| Right hand fixing hair (RH FH) | 0.50 | 0.31 | 1.62 |

Table 4.10: GLMM model for hand asymmetry (right vs left frequency of hands scratching)

| | Estimate | Std. Error | z value |
|---|---|---|---|
| Right hand scratching (RH Scr) | -0.13 | 0.08 | -1.60 |

Table 4.11: GLMM model for hand asymmetry (right vs left frequency of hands holding a drink)

| | Estimate | Std. Error | z value |
|---|---|---|---|
| Right hand drinking (RH Dr) | 27.95 | 14.49 | 1.93 |

The following graph 4.17 shows the number of times people perform the three actions (hands still on face, hands moving on face and communicative hand gestures) throughout the performance. The x-axis represents the timeline of the performance in seconds and it starts approximately three minutes before the beginning of the performance and the y-axis the number of times people perform the gesture. From the tree plots, it is clear that people perform more communicative gestures (wave their hands while speaking) before the beginning of the performance when they interact or talk with each other while during the performance they mostly have their hands still on their faces. Hand behaviours such as scratching or drinking are periodically performed during the performance.

Taking a separate look at the still and moving on face gestures across the whole performance, the graph below shows that as the time of the performance progresses there are more hands still on people's faces while there is a periodic pattern in the moving hand to face gestures.

Another interesting finding that is apparent from this plot is the behaviour of the people during the pre-performance part (see section 3.2 for more details about pre-performance). During this part, it appears that people needed some time until they realised that the first performer was on stage, this is the reason why they kept performing communicative gestures until they realised that the performance has started.

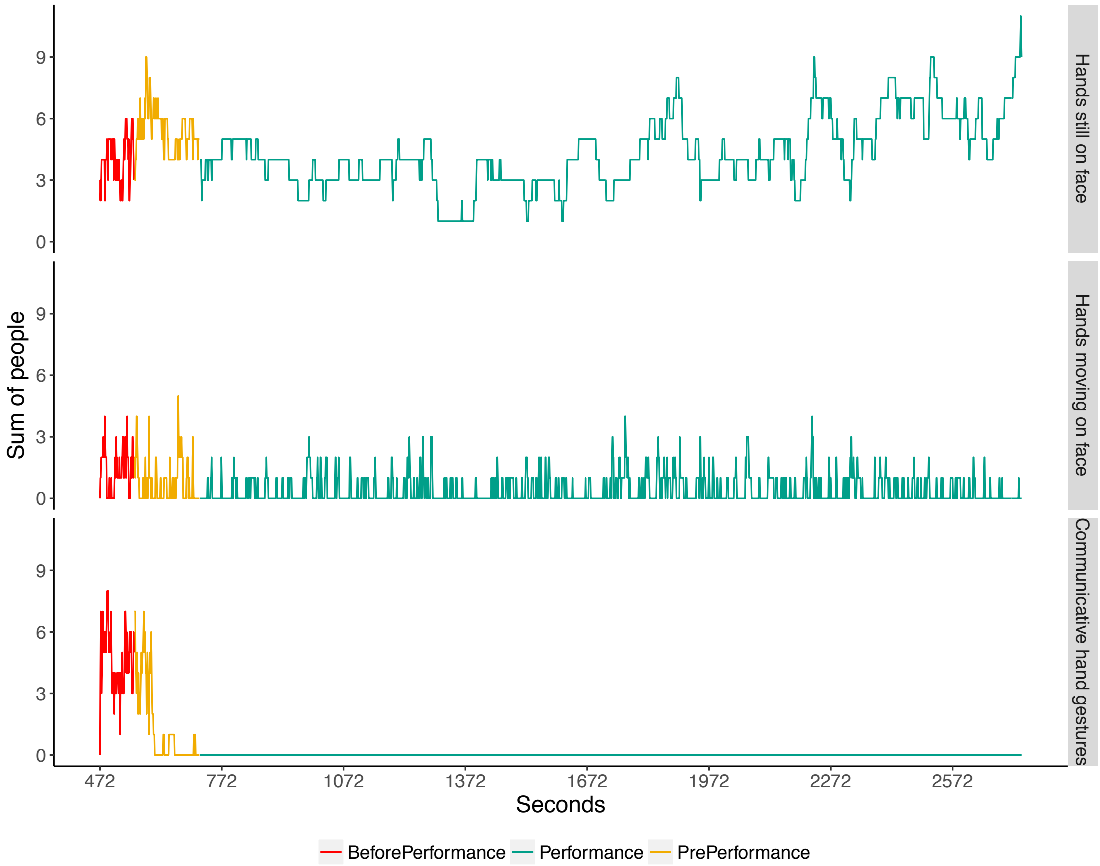


Figure 4.17: Number of people performing the actions before and during the performance

### 4.4.3 Audience body movement

This section of the analysis includes the average velocity data extracted using the optical flow algorithm. Figure 4.18 below shows the average velocity of the audience for the whole duration of the video, starting before the performance and finishing with the applause of the audience members. Looking at the performance part only (figure 4.19), it appears that there is a tendency for a decrease in the average velocity of the audience's movements as the performance progresses. In addition, the plot seems to indicate that there is more movement in the audience before the performance and during the applause sections while the movement is limited during the performance.

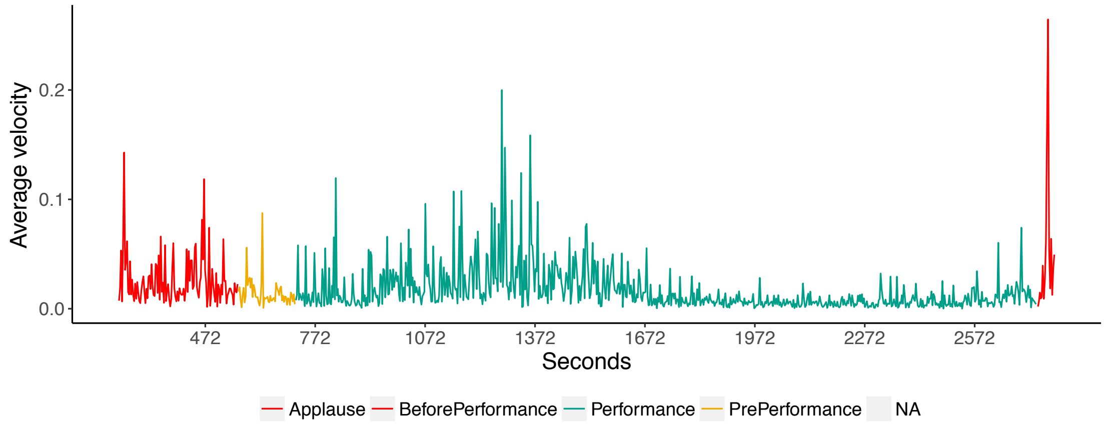


Figure 4.18: Average velocity of the audience before, during and after the performance

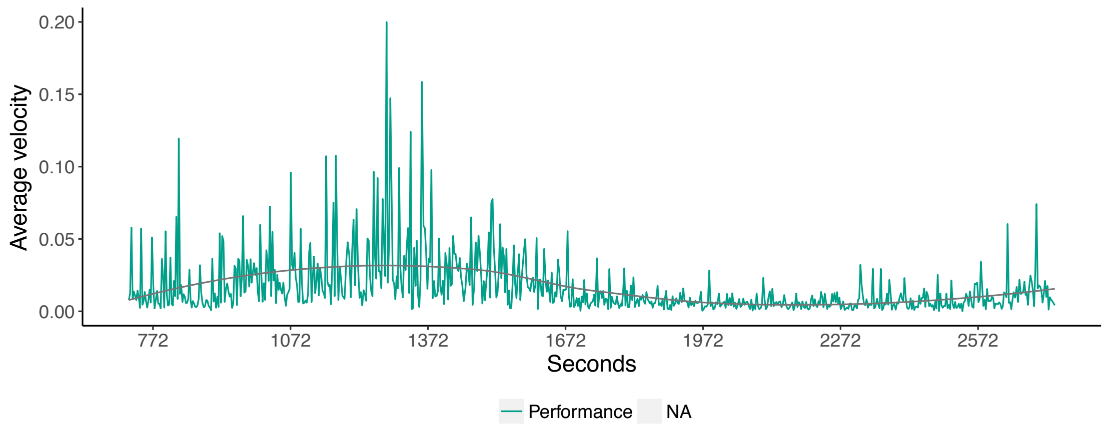


Figure 4.19: Average velocity of the audience during the performance. Trendline was calculated using a generalized addictive model

This is more clearly depicted in the box-plot in figure 4.20 below which shows the median values of the average velocity of the audience members during each section. To test for any significant differences among the parts a generalised linear model (GLM) with a lognormal distribution (see distribution fit in appendices A) was used. For data simplicity the four parts were grouped in two broader ones. "Applause" and "Before performance" parts were added together into a section named "Non-performance" while "Pre-performance" and "Performance" parts in a section named "Performance". Results show that there is more movement in the audience during the "Non-performance" part while during the "Performance" audience movement decreases (Chi-sq=33.8, $p<0.01$). Planned pairwise comparisons of the four performance states show that the average movement during the applause is significantly different compared to all the other parts (Before performance - Applause, $p<0.001$, Performance - Applause, $p<0.001$, Pre-performance - Applause, $p<0.001$). The average velocity of the audience is significantly less during the performance compared to before the performance (Performance - Before performance, $p<0.001$) while movement during the pre-performance is significantly lower compared to the part before the performance (Pre-performance - Before performance, $p<0.03$). Finally, the results do not show any significant difference in the audience responses between the performance and the pre-performance parts (Pre-performance - Performance, $p= 0.89$).

Table 4.12: GLM model for average velocity (performance vs non-performance)

| | Estimate | Std. Error | t value |
|---|---|---|---|
| During Performance | -0.56 | 0.08 | -6.66 |

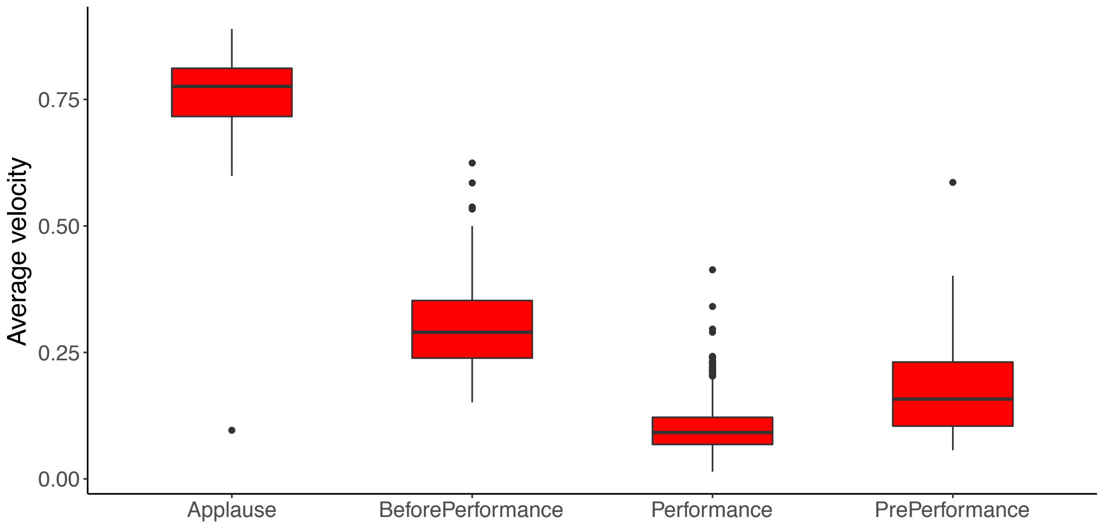


Figure 4.20: Box plot of the median values of audience body movement before the performance, during the pre-performance and during the performance

Table 4.13: Pairwise comparisons for the average velocity of the audience during the four performance states

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Before performance - Applause | -0.66867 | 0.13499 | -4.953 | <0.001 |
| Performance - Applause | -1.10095 | 0.11915 | -9.240 | <0.001 |
| Pre-performance - Applause | -1.24579 | 0.23080 | -5.398 | <0.001 |
| Performance - Before performance | -0.43228 | 0.09465 | -4.567 | <0.001 |
| Pre-performance - Before performance | -0.57712 | 0.21916 | -2.633 | 0.03 |
| Pre-performance - Performance | -0.14484 | 0.20977 | -0.690 | 0.89 |

### 4.4.4 Audience - Dancers Interaction

To test for the presence of a global relationship between audience and dancers body movements, a Spearman's rank-order correlation was applied. For this, the average velocity of the audience was compared with that of the dancers. The part of the performance was only tested removing from the timeseries of the audience the parts before and after the performance.

The results show that there is a positive correlation, which is statistically significant ($r = .142$, $p < .001$). This suggests some sort of mutual influence between the dancers and audiences' movements, which is an interesting outcome. However, correlation just looks at the global relationship of the two timeseries and not on possible interactions that occur in different times during the performance. The primary goal here is to determine if dancers movement predicts audience movement during the performance. To do this Granger Causality (GC) analysis as described in the section 3.6.1 of Chapter 3 was applied. GC accounts for the presence of autocorrelations and is able to identify meaningful lagged relationships between two timeseries at different timescales (Dean and Bailes, 2010).

This was examined for the duration of the performance and for lags between -9 and +9 seconds and assessed GC relationships at temporal delays between 1 and 9 seconds. Positive lags indicate dancers movement predicting audience movement while negative lags indicate the opposite. To ensure stationarity, all time-series were differenced by subtracting consecutive sample points from each other (e. g. dAudience.averagevelocity = Audience.averagevelocity2-Audience.averagevelocity1) prior to applying GC.

As seen in plot 4.21 below the results show no significant GC relationships between audience and dancers average velocity during the performance (p at all lags $> .05$).

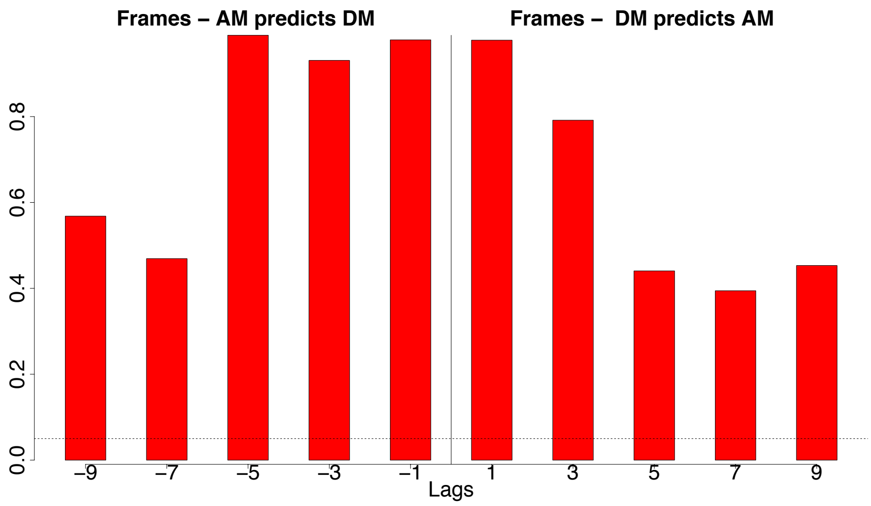


Figure 4.21: GC for audience movement (AM) and dancers movement (DM) during the performance. The x axis indicates the lag order in seconds and the y axis the p values. The dashed line indicates a significance level of p .05

### 4.4.5 Interview: Moments of Dramaturgy

Finally, this section presents the results during the moments of dramaturgy mentioned by the choreographer. A dramaturgic moment in contemporary dance shows the development of ideas over the piece, their order and structure (Whitley, 2015). Dramaturgy is a comprehensive exploration of the context in which the play resides. It enters contemporary dance at the same time as the changes in European contemporary dance that have been taking place from since 1980s. It is the art of dramatic composition for dance. When we talk about narrative pieces, the word "dramaturgy" refers to the storyline. In dance, dramaturgy is considered to be the basic structure that gives shape to the piece [1].

As described above, "Frames" is a contemporary dance piece that focuses on the manufacturing of objects as well as the manufacturing of experiences in the context of a theatre and how people can organise such processes (Whitley, 2015). In terms of the general concept and structure of "Frames", during the interview Whitley explained that the first part of the piece has a linear process within which the dancers sort and put together the metal structures while on the other hand, the choreography follows a non-linear process where the dancers start to play with the things they constructed, exploring the possibilities of them.

The performance starts with a short section (pre-performance) during which a dancer comes on and off the stage very informally arranging things. According to Whitley (2015), during the performance in Glasgow this part of the piece wasn't successful because the stage curtain went up just before the dancer appeared on stage, as soon as the curtain went up the audience stopped talking and started observing what was happening on the stage.

> "It should be much more of a background thing that you don't really pay that much attention to. The idea should be that you come in to your seat and you see that something is happening but you still kind of chatting and not paying full attention to that in the way that they do when the houselights go down. That allows the audience to get familiar with the space before the performance. I was much more interested in that black space being there for the audience to witness and experience in a way that it was not just a big reveal of a thing." (Whitley, 2015)

Following this part, the music starts, the lights turn off and the performance begins properly with a solo dance. According to Whitley, this introduction into the dance is the first significant moment in the performance. The idea with this section was that it was deliberately virtuosic display of the possibilities of what a person can do with a piece of metal. It launches you straight in into high level dramatically and he goes off in this kind

[1] https://www.contemporary-dance.org/movement-dramaturgy.html

of a share of tricks with the pole so what follows from that has the effect of. After the solo, the other 11 dancers show up on stage and the section called 'sorting' begins. During the performance the dancers use the frames to build up different shapes and controlling them with their bodies and in collaboration with the other dancers. The performance ends up with the frames hanging from the ceiling and the dancers performing a final choreography with quite tense music.

Based on the moments reported by Whitley in the second part of the interview, the section below focuses mainly on these specific moments of dramaturgy and their relationship to the audience responses. According to Whitley, the role of dramaturgy in dance is quite significant. Whitley was advised on the dramaturgic part of the piece "Frames" by the performing arts curator and producer of Sadler's Wells Eva Martinez. Martinez's advice gave answers to questions about how evident or visible Whitley's ideas are on the piece and also how the strength of those ideas come across in relation to how they arranged, this has mostly to do with the sequencing and the length of these ideas. One last thing that Whitley mentioned during the interview and it is worth mentioning here is that of interludes. According to Whitley interludes are moments of the performance that help the audience and the performers to progress from one section to the other. There are periods in between the choreography during which the dancers organise the stage for the next choreographical section to begin but are more functional than aesthetic and are expected to be less engaging.

The rest of this section focuses on the effect that interludes and dramaturgic moments mentioned by Whitley might have on the audience.

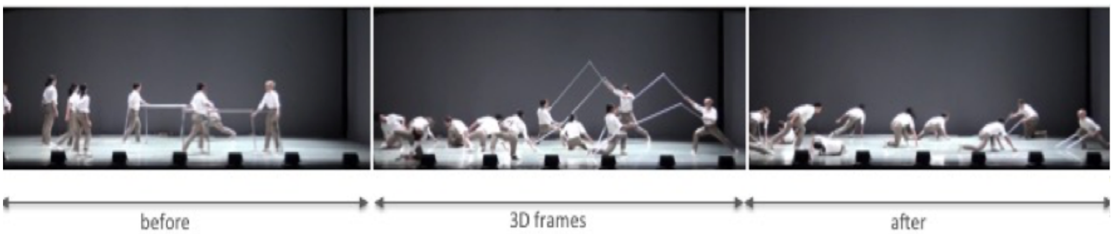


Figure 4.22: 3D Frames: first dramaturgic moment in "Frames"

The first dramaturgic moment in "Frames" according to Whitley is a transition during the performance in which the metal structures suddenly change shape. The frames converted from a rigid rectangular shape (similar to the shape of a table) to a wavy 3-dimensional shape. For the sake of data simplicity we will call this moment "3D frames".

In the interview Whitley says:

> "The idea that the table section holds for long is to have a dramatic visual effect. It will be something really unexpected; you are getting used to the

idea of frames being in that shape even if the dancers are doing different things with them." (Whitley, 2015)

"It was more of the possibilities of what the frames could do, to make different shapes etc. it creates an immense volume in the stage." (Whitley, 2015)

Whitley expects the audience to be affected during this moment because he considered it as an unexpected moment that creates a striking image. To test this, a generalised linear model (GLM) with a lognormal distribution of the average velocity of the audience as a function of three phases of "3D frames" (before "3D frames", during "3D frames", after "3D frames") was used. Each of the two phases before and after "3D frames" was generated by subtracting and adding six seconds before and after the moment respectively. The model shows a marginal overall effect of phase on the average velocity of the audience (Chi-sq=5.978, p=0.06). Planned pairwise comparisons do not show any significant difference in the average velocity of the audience immediately before or after the dramaturgic movement, but the results show that the audience was moving more during the period before the dramaturgic moment compared to the period that followed.

Table 4.14: GLM model testing the effect of 3D Frames phase on the average velocity of the audience

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| After 3D Frames -3D Frames | -0.1707 | 0.2162 | -0.789 | 0.70 |
| Before 3D Frames -3D Frames | 0.2188 | 0.1866 | 1.173 | 0.46 |
| Before 3D Frames -After 3D Frames | 0.3895 | 0.1693 | 2.301 | 0.05 |


Figure 4.23: lights-off: Second dramaturgic moment in "Frames"

The second dramaturgic moment came at the end of the performance. At this moment the stage goes completely dark. In the section just before this dramaturgic moment, the dancers are performing by holding the metal frames together with a light placed on them. All the other lighting on stage and around is completely off. At the end of this part the dancers place the metal frames on the floor with the lights facing downwards and the stage goes completely dark. This is a very significant moment for Whitley since as he said in the interview it is not used to move people around but to create a dramaturgic effect (Whitley, 2015).

Similar to first dramaturgic moment, its effect on the audience was tested in a GLM with a lognormal distribution. The model does not show any effect of the dramaturgy phase on the average velocity of the audience (Chi-sq=0.72, p=0.69).

Table 4.15: GLM model testing the effect of total darkness on the average velocity of the audience

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Before lights-off - After lights-off | 0.03971 | 0.08709 | 0.456 | 0.89 |
| lights-off - After lights-off | 0.07840 | 0.09217 | 0.851 | 0.67 |
| lights-off - Before lights-off | 0.03869 | 0.09038 | 0.428 | 0.90 |

Finally, all the interludes mentioned by Whitley during the interview were separated and audience reactions were examined six seconds before, during and six seconds after each interlude. The model does not show any effect for the first (Chi-sq= 4.6568, p=0.09) and the third interludes (Chi-sq=0.36, p= 0.8) while results show an effect for the second (Chi-sq= 10.116, p=0.006) and the fourth (Chi-sq=18.117, p<0.001).

In particular, for the second interlude, planned pairwise comparisons show no difference before and during the second interlude (before vs during, p=0.26) and between the sections before and after the interlude (before vs after, p=0.30) but a significant difference is found during and after the interlude with an increase in the velocity of the audience after the interlude (during vs after, p<.01).

In the fourth interlude, there was a significant increase in the velocity of the audience during the interlude (before vs during, p=0.03) but a significant drop appeared after the interlude (during vs after, p<.01).


Figure 4.24: Four Interludes reported by Whitley

Table 4.16: GLM model testing the effect of Interlude 1 on the average velocity of the audience

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Before interlude 1 - After interlude 1 == 0 | 0.20139 | 0.16700 | 1.206 | 0.44 |
| Interlude 1 - After interlude 1 == 0 | -0.09289 | 0.14640 | -0.635 | 0.79 |
| Interlude 1 - Before interlude 1 == 0 | -0.29428 | 0.12752 | -2.308 | 0.05 |

Table 4.17: GLM model testing the effect of Interlude 2 on the average velocity of the audience

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Before interlude 2 - After interlude 2 | -0.1775 | 0.1201 | -1.478 | 0.30 |
| Interlude 2 - After interlude 2 | -0.3788 | 0.1199 | -3.160 | 0.004 |
| Interlude 2 - Before interlude 2 | -0.2013 | 0.1296 | -1.553 | 0.26 |

Table 4.18: GLM model testing the effect of Interlude 3 on the average velocity of the audience

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Before interlude 3 - After interlude 3 | -0.04784 | 0.10371 | -0.461 | 0.88 |
| Interlude 3 - After interlude 3 | -0.05230 | 0.08846 | -0.591 | 0.82 |
| Interlude 3 - Before interlude 3 | -0.00446 | 0.09229 | -0.048 | 0.99 |

Table 4.19: GLM model testing the effect of Interlude 4 on the average velocity of the audience

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Before interlude 4 - After interlude 4 | 0.11811 | 0.13683 | 0.863 | 0.65 |
| Interlude 4 - After interlude 4 | 0.35418 | 0.10800 | 3.280 | 0.002 |
| Interlude 4 - Before interlude4 | 0.23607 | 0.09664 | 2.443 | 0.03 |

## 4.5 Reflective Summary

This chapter presents an initial quantitative exploration of the overt responses that occur in an audience during a live dance performance. This study works as a baseline for the following chapters since it introduces some of the main methods that are used in the following two studies. Most importantly its findings define the hypotheses and experimental design for the following studies.

An overall analysis and discussion, incorporating the results of all three studies, is provided in a dedicated chapter (Chapter 7) along with possible implications, and an overall assessment of the methodological approach, based on the findings and experience gained throughout the whole research process.

In general, the results show that the clearest overt audience response is applause at the end of the performance while social interaction and especially talking is definitely suppressed during the performance. The most obvious finding of this study, apparent from even a casual inspection of the video footage is that audiences move very little and have predominantly expressionless faces during the performance while the most salient identifiable movements that could be potentially visible to the dancers, are those of bringing the hands up to the face.

Audience blank faces and decrease of movement during the performance comes in clear contrast to the animated facial expressions and body movements that are apparent before and after the performance. This observation is underlined by a feature of "Frames" in which the opening sequence (pre-performance) is designed to be ambiguous as to whether the performance has actually started. The audience movements and expressions observed during this opening sequence are correspondingly mixed possibly reflecting an uncertainty in the audiences' responses to what is happening on stage. This lack of audience expression might be connected to the fact that audiences are not considered socially engaged during the performance while when lights turn on audiences start interacting with each other. This finding is consistent with the research of (Kraut and Johnston, 1979; Fernandez-Dols and Ruiz-Belda, 1995) about the social messages of smiling and comes in contrast with the emotional hypothesis of smiling (Darwin, 1956). We speculate that in the context of a social interaction a blank face can easily be interpreted as angry. However, it may be that during the performance people do not consider themselves to be actively socially engaged and in this context a blank face is more plausibly interpreted as a sign of attention or concentration. This finding is tested again in the following study and is discussed further in Chapter 7.

The observation that the audience moves very little during the performance brings into question of what, if anything, can the dancers detect from a "live" audience. One possible answer from the data provided above is aggregate audience movement. This aggregate movement could be something that the dancers can detect - possibly unconsciously - as a signal of how engaged the audience is with their ongoing performance.

More specifically, based on the graphs presented above the general movement of the audience decreases as the performance progresses while there is an increase in the number of the hands that are still on the face. This finding shows that people become increasingly still over the duration of the performance. If people do become progressively stiller over the duration of the performance this raises the question of whether it is actually the lack of movement that is a key signal of how engaged people are in the performance. This association of stillness with engagement will be tested in the two following studies using a more focused methodological approach. In particular studies 2 and 3 will test the following hypothesis: Movement and engagement are inversely correlated.

Following the audience aggregated movement analysis, the detailed analysis of the hand to face gestures shows that during the performance audiences use their hands to perform activities such as scratching, fixing hair or drinking, while the duration that peoples' hands were down appears to be equal to hands being still up on the face. These activities suggest that audience hands is the part of the body that moves more frequently during the performance and may be one of the signals that the audience unconsciously provide to the performers. This suggests the following hypothesis: Audience hand movements provide a specific, distinct and salient response cue to performers that will be tested in the second study (Chapter 5).

An unexpected result from the hand gesture analysis, is that people have their left hands up considerably more times compared to the right hands while only the right hand is used for holding a drink. However, some caution is required in interpreting this result since there is no information about audiences handedness. This is quite an unexpected finding since only 12% of the world's population are left-handed. One possible explanation but quite an unlikely reason for this may be that people hold a drink with their right hand and the left hand is the one free to move. However, this assumption is not supported by the low number of people drinking during the performance.

In addition, even though the results show a global correlation between audience and dancers aggregated velocity, granger causality (GC) analyses do not show any significant relationship between the two. This finding is in contrast to the kinaesthesia hypothesis discussed in Chapter 2 and brings up questions relevant to other aesthetic elements of a dance performance such as the audio or the stage lighting. Is movement the most important element of a dance performance and the one that might affect the audience? However, as mentioned before some caution is required in interpreting this result due to the low accuracy of the synchronisation of the two videos (performance, audience). The interaction between audience movement and elements of the performance such as audio and visual projection is further tested in the following two studies (Chapters 5,6).

Finally, contrary to expectations, this study found only some marginal evidence that audience responses differ before and after the two dramaturgic moments mentioned by the choreographer. This finding questions whether dramaturgic moments are the right moments to test for changes in audience responses or changes in audience engagement. It also questions meaning of choreography in contemporary dance and suggests that the important transitions identified by choreographers might not necessarily evident to audiences.

In addition, an interlude seems an important moment both for the performers but also for the audience. The results show that during one out of the four interludes mentioned by Whitley audience movement increases. This interlude differs from the other three since no choreography takes place on stage but instead the dancers are assembling a metallic structure under dimmed lighting conditions. This increase of movement in the auditorium suggests that audiences might use this interlude as an opportunity to disengage from the performance and reorganise their bodies. This result brings many questions on how long it takes for someone to respond to a stimulus and even if audience responses correspond to the ones expected from the choreographer of the piece. Is the audience able to identify when an interlude takes place during a performance? Maybe these choreographic distinctions are likely to be more important and as a result more recognisable by expert audience members.

# Chapter 5

# Audience responses Part II: A closer look at hand movement

## 5.1 Introduction

Informed by the findings of the first study, this chapter presents the second study on live audiences and focuses on testing specific hypotheses relevant to audience hand, face and body expression during a live performance. To begin with, the general face, body and hand behaviour patterns displayed by the audience are mapped out, followed by a closely considered detailed analysis of the potential relationship between engagement and body movement. In particular, the following hypotheses will be tested:

***Hypothesis 1 (H1):*** *Audience hand movements provide a specific, distinct and salient response cue to performers*

***Hypothesis 2 (H2):*** *Movement and engagement are inversely correlated*

***Hypothesis 3 (H3):*** *Audience movement can be predicted from dancers movement.*

The study took place on the 17th of March 2016 at The Place theatre in London where four contemporary dance pieces were performed by the postgraduate students of the London Contemporary Dance School (LCD). Informed by the methods and techniques discussed in the previous chapter, continuous quantitative measures were extracted from recordings of the audiences and the dancers. In a similar way to the previous study, this study tries to uncover the overt reactions of a live audience (Facial expressions, Body movements and Hands movements), interpret moments of stillness and take a closer look to the audience hand responses. A detailed description of the methodological approach as well as a broad analyses of the data are undertaken, and findings are reported below.

## 5.2 Performances by London Contemporary Dance School

The Place is a creative house for dance development that includes dance training, creation and performance. It is home to the London Contemporary Dance School (LCD) and the Richard Alston Company. The theatre can accommodate up to 280 people and presents over 200 performances a year (See figure 5.1).

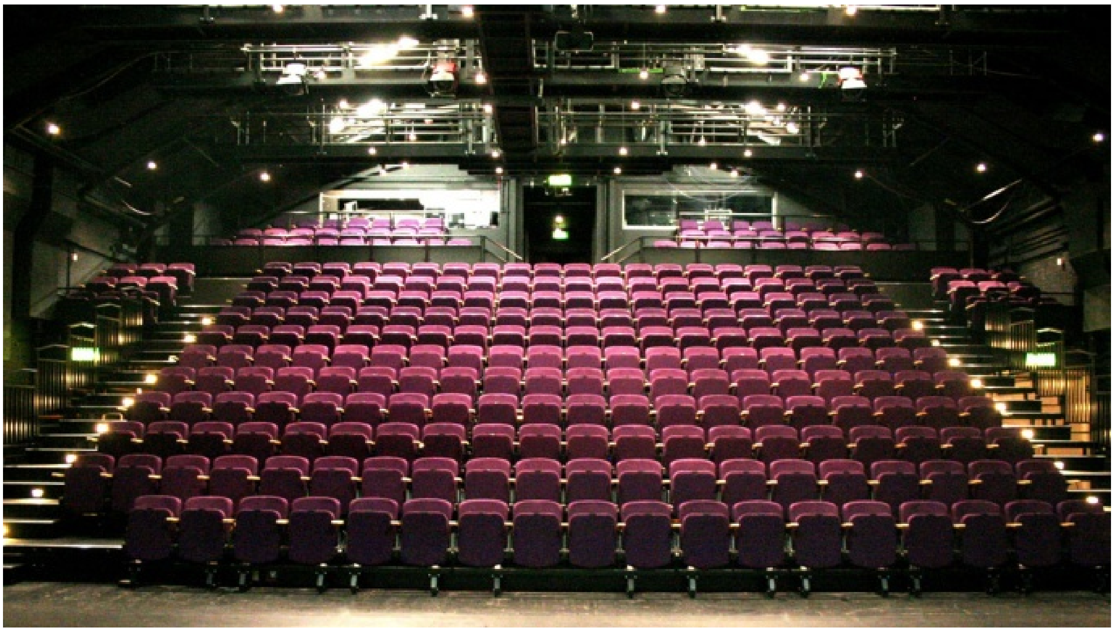

Figure 5.1: The Place theatre

The performance that was analysed in this study lasted for one hour and forty minutes and consisted of four twenty minute dance pieces (see figure 5.2). There was a fifteen minute interval between the second and the third piece and two three minute interludes after the first and the third piece. Each dance was performed by LCD postgraduate students and directed by commissioned professional choreographers. The first piece, "Les femmes meurent deux fois" was directed by the choreographer Danae Morfoniou. This piece starts with a pre-performance part during which the lights are turned off, the music starts but there are no dancers on stage. When the music stops, the dancers appear on stage and start performing the first choreographic piece without the accompaniment of music. The second piece "Triptych", was directed by Mara Vivas. This is the quietest among the four pieces since for the majority of the time the dancers perform synchronised, gentle movements in silence. The third performance is called "The Endgame" and was directed by the choreographer Olatz de Andres. In comparison to the other three, this piece includes different theatrical effects and many artistic changes (lighting and music changes). The fourth performance,"The Tide" was directed by Tom Roden. In addition to the dancing part, this piece also includes some acting parts. There is no dialogue among the dancers but a narrator is on stage during most of the performance. As part of the study on audience responses, the audiences as well as the dancers were filmed during the four parts of the performance. More detailed information of the performances including the names of all the dancers that performed can be found in appendix B.

Figure 5.2: Performances Part 1 to Part 4 (from left to right) performed by LCD

## 5.3 Materials and Methods

### 5.3.1 Data capture: Equipment and technical specifications

In order to be able to capture a larger audience sample size of the audience compared to that of Study I, two Basler Ace (1280x1024px resolution) night vision cameras (45fps) were used. An infrared light (IR) was attached on top of each camera to allow the filming of the audience during the dark periods of the performance. Both cameras and IR lights were placed on the theatre truss on top of the stage pointing towards the part of the audience that was going to be filmed (See figure 5.8). The camera lenses available varied in size which determined the position of each camera, the first camera had a 16mm (23.99° angle) and the second 25mm (15.49° angle) focal length. In order to achieve the maximum possible resolution for each person and keep a similar resolution for each camera, the camera with the smaller angle was placed on the first rig while the wider angle camera was placed on the second rig. As a result, the 23.99° angle camera was able to film a range of 21 audience members while the 15.49° angle camera could capture 17 audience members. The dancers were also filmed using a JVC professional camera (29.97fps) which was hanged from the rig facing the stage. For the synchronised double GEV camera recording, the Gecko software made by Vision Experts was used. Gecko gave better data accuracy since it provided a timestamp on each frame. This helped to avoid any synchronisation problems and improve the accuracy of the results compared to those of the first study.

Apart from the video recording of the audience and the dancers, the recordings specifically aimed to collect continuous hand (wrist) movement data for each audience member. For this purpose, a number of wristbands were made out of 5mm reflective rope. A small plastic bag with two reflective wristbands together with instructions on how to wear them was placed on the arm of each theatre seat (See figure 5.8). Each audience member had to wear one wristband on each hand. As the IR lights were facing directly on the audience, the wristbands became very visible in the video recordings. Multiple solutions were researched and identified in order to automatically track and record continuous wrist movements, this solution was the cheapest and easiest for the budget and time available for this project.

Privacy was also an issue as one of the aims of this study was extract personal data from the audience members. The study was certified with an ethical approval from the Ethics Committee of Queen Mary University of London (Ethical approval reference number: QMERC1432a) and a sign was placed on each seat to inform audience members that filming was taking place during the performances for research purposes. (see Appendix B for the Ethical Approval). The sign on the seats read as follows:

*'Please note: Researchers from Queen Mary University will be filming sections of the audience as part of a study into audience behaviour during contemporary dance performances. Audience members seated in the research area who do not want their image to contribute to the data should speak to the duty manager before the performance or may contact:l.theodorou@qmul.ac.uk at a later date.'*

### 5.3.2 Continuous Dataset: Audience and dancers

Similar to Study I, data analysis techniques developed in computer vision research, were used to obtain fine-grained response measures from the footage of the audience and dancers. The data processing pipeline (See figure 5.8) consisted of: **1.** Blob detection algorithm from the Blobscanner Processing library (Molinaro, 2010) used to detect and extract the continuous position of the wrist of each audience member **2.** Optical flow algorithm made by Greg Borenstein (Borenstein, 2013) in Processing used to calculate the visual change in both the footage of the audience and the dancers **3.** SHORE$^{TM}$ a facial analysis software made by the Fraunhofer Institute (Küblbeck and Ernst, 2006) for Integrated Circuits used to extract all the facial expressions of each audience member during the performance (more detail on SHORE$^{TM}$ in section 4.3.2).

#### Visual edits

VirtualDub software was used to read the series of numbered images as a video stream and downsample the data from 45fps to 29.97fps in order to synchronise it with the dancers recording. ELAN, a professional tool for the creation of complex annotations on video resources, was used to synchronise the three videos together (two videos of audiences and one of the performance). Due to the timestamp and to the stable framerate, this time the synchronisation was more accurate and easier to compare here rather than in the 1st study (See figure 5.3).

Figure 5.3: Synchronised footage of audience and dancers

**Average velocity of the dancers and audio power of the performance**

Apparent average velocity in the video recording of the performance was measured using the optical flow algorithm. Similar to the first study the version of optical flow used was based on the algorithm presented in (Farnebäck, 2003). In particular, we relied on the OpenCV for Processing implementation made available by Borenstein (2013). In order to achieve a more finer grained analysis and better accuracy, the algorithm had to be modified to be able to extract the average velocity from the video for every frame, ended up with a dataset of 29 fps. This improvement was applied to all the computer vision techniques described below. For more information about optical flow see section 4.3.2.

Apart from the movement on stage, the power of the soundrack for each part of the performance was calculated using the miraudio toolbox for Matlab (Lartillot and Toiviainen, 2007) and an operator called Root Mean Square (RMS).

### Audience upper body movement

Optical flow was also used to estimate the average upper body velocity of each audience member separately. This included the head, the torso and the hands. Specifically, a static polygonal envelope was drawn around each audience member (See figure 5.6) and the magnitude of optical flow was integrated over each of these envelopes. This method is based on the assumption that during a performance seated audience is only able to move in a limited area; motion outside the envelope would not contribute to the integral. This can reduce the accuracy of the results in some cases but it was an easy way to extract individual movement from the audience.

### Audience hand movement

The use of the wristbands was very important for the detection of hand motion as was the use of the blob detection algorithm provided by the Blobscanner library for Processing (Molinaro, 2010). The algorithm is based on connected component detection and brightness thresholding; the threshold was set manually based on the observation that the reflective wristbands stand out in the images as regions of high intensity under infrared illumination (See figure 5.7). By applying this method to each frame it was possible to extract the image coordinates of all the wristbands, which allowed the right and left wrist positions of each of the audience members to be tracked.

Due to pose changes and self occlusions a completely automated tracking throughout the performance was found to be unreliable. It was therefore considered best to use the algorithm to obtain an initial set of traces that were subsequently overlaid on the footage of the entire performance and corrected or disambiguated manually as required. In order to remain consistent and also to capture information from the hands proper, we chose not to differentiate the coordinates of the wristbands directly. Instead, the continuous position of the wristbands was used to anchor a rectangular neighbourhood covering the region of each hand. The magnitute of the optical flow field was then intergrated frame by frame over these hand regions to obtain an estimate of the average velocity of the hands.

### Audience head and torso movement

In order to be able to separate the contribution of hand movements in the performance, their behaviour was compared with that of the rest of the body. In order to isolate the head and torso movement of each person in the audience the magnitude of the optical flow field was intergrated over the polygonal envelope defined above minus the hand regions identified (see images in Figure 5.4). In this area optical flow was applied again.

Note that this is not equivalent to a simple difference of the time series computed in the above sections, as the hand regions may or may not overlap with the static envelope. This process gave us an estimate of the upper-body movement of each person excluding hand movements.

### Audience facial expressions

Audience facial expressions were extracted using the same computer vision framework (SHORE$^{TM}$) used in Study 1. For more details on this see section 4.3.2 in Chapter 4.

Figure 5.4: Optical flow calculating body movement excluding the hands

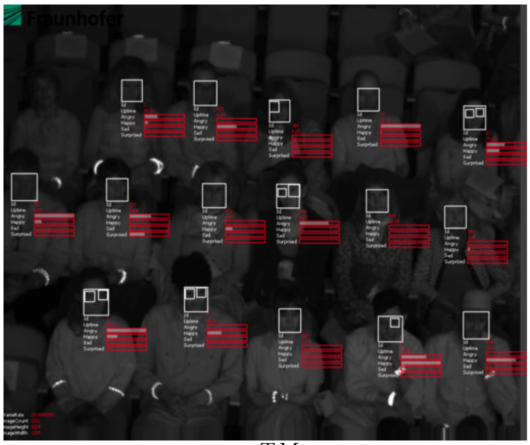

Figure 5.5: SHORE$^{TM}$ software tracking facial expressions

Figure 5.6: Polygonal envelope drawn around each audience member

Figure 5.7: Blob detection tracking hand movement

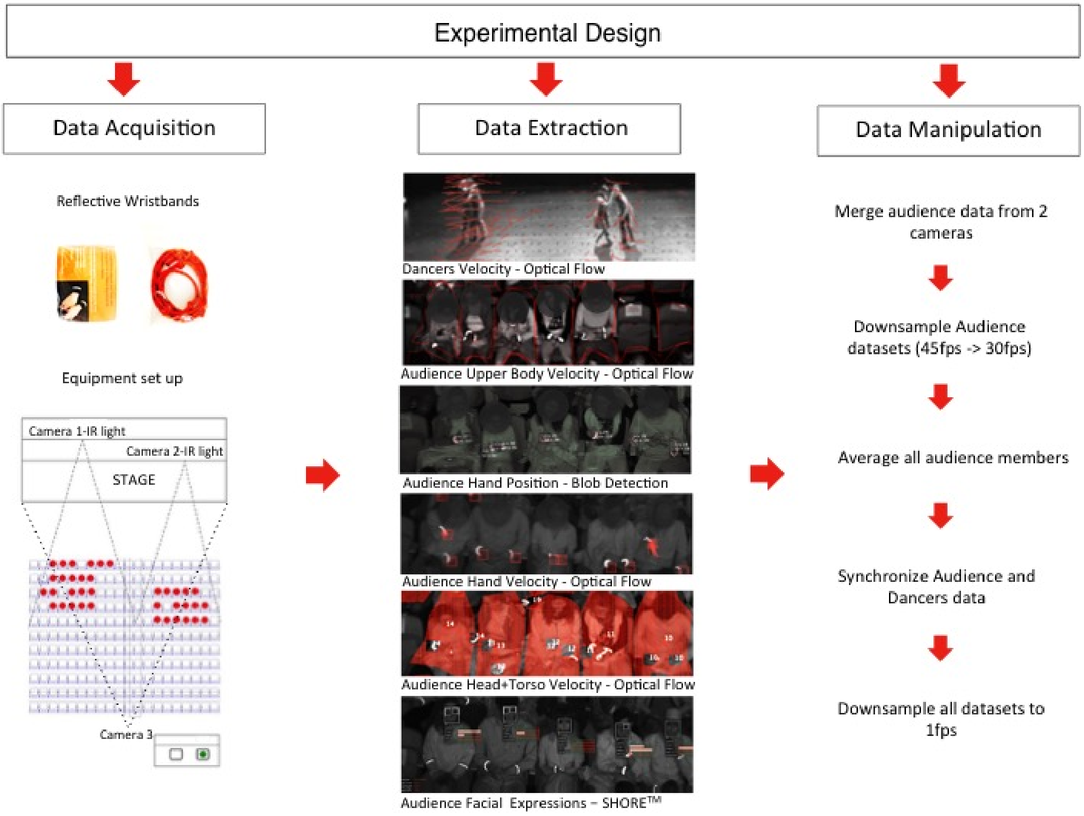


Figure 5.8: Study II: Data collection and data processing pipeline

### Data preprocessing

For data analysis purposes the audience data recorded from both cameras was merged into one data set. The two video recordings together collected data from a total of 48 audience members. However the sample size of each data set varied depending on the tracking method used to export the data (see results section for details). In summary, seven timeseries variables were calculated for each performance part. Two were extracted from the performance: the average velocity that was produced on screen (described in section 3.2.1) and the audio power of the performance. Five timeseries variables were derived by averaging the spectators following datasets: facial expressions (displayed anger and happiness), velocity of the hands, head and torso and total upper body. It was decided that a sampling rate of 1Hz for the compiled data set was appropriate given earlier studies (Schubert, 2004), which indicate that real-time perceptual responses generally take at least 1 to 5 seconds for full registration.

| Frame | Time.Sec | Performance | Avg.Dancers.X | Avg.Dancers.Y | Avg.Dancers.Speed | Avg.Audience.X.Ch1 | Avg.Audience.Y.Ch1 | Avg.Audience.Speed.Ch1 | Avg.Audience.X.Ch2 | Avg.Audience.Y.Ch2 | Avg.Audience.Speed.Ch2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 26375 | 00:14:39 | Part_1 | 0 | 0 | NA | -0.034055315 | -0.011116812 | NA | -0.014410461 | -0.003420463 | NA |
| 26405 | 00:14:40 | Part_1 | 0 | 0 | 0 | 0.005188976 | 0.005944486 | 0.011552483 | 0.000173781 | 0.002964197 | 0.007567496 |
| 26435 | 00:14:41 | Part_1 | 0 | 0 | 0 | 0.000666095 | 0.000224781 | 0.001821387 | 0.005341968 | 0.005826887 | 0.007678992 |
| 26465 | 00:14:42 | Part_1 | 0 | 0 | 0 | -0.000172717 | 0.007537954 | NA | 0.005359908 | 0.008952278 | 0.004074652 |
| 26495 | 00:14:43 | Part_1 | 0 | 0 | 0 | -0.005725045 | -0.003016352 | 0.009086207 | 0.002639514 | 0.000477497 | 0.001278109 |
| 26525 | 00:14:44 | Part_1 | 0 | 0 | 0 | -0.003488075 | 0.00295459 | 0.009517177 | 0.001458685 | -0.022107797 | 0.023178534 |
| 26555 | 00:14:45 | Part_1 | 0 | 0 | 0 | 0.003440315 | 0.001281151 | 0.016564376 | -0.001407173 | -0.003749253 | 0.02248683 |
| 26585 | 00:14:46 | Part_1 | 0 | 0 | 0 | -0.007083584 | -0.008672676 | 0.012337955 | -0.000759674 | 0.001118123 | 0.000151173 |
| 26615 | 00:14:47 | Part_1 | 0 | 0 | 0 | -0.00193186 | -0.003766749 | 0.006415691 | 1.74E-05 | 0.00048922 | 0.000241054 |
| 26645 | 00:14:48 | Part_1 | 0 | 0 | 0 | 0.000332516 | 0.000442203 | 0.005184078 | 4.15E-06 | -8.14E-06 | 0.000100532 |

Figure 5.9: 1st Dataset: Average dancers and audience body movement

| Frame | Person | Performance | Time.Sec | Body.Mvm.X | Body.Mvm.Y | Body.Mvm.Speed | Left.Hand.X | Left.Hand.Y | Left.Hand.Speed | Left.Hand.behavior | Right.Hand.X | Right.Hand.Y | Right.Hand.speed | Right.Hand.behavior | Hands.Speed | Multiplier(Body.Mvm.X/Hands.Speed) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 26375 | 1 | Part_1 | 00:14:39 | -0.024957935 | -0.028014484 | NA | 1221.25 | 978.75 | NA | 0 | 1098.78296 | 851.05376 | NA | 1 | NA | NA |
| 26405 | 1 | Part_1 | 00:14:40 | -0.002791821 | 0.024911417 | 0.033649258 | 1221.25 | 978.75 | 0 | 0 | 1098.13274 | 857.8638737 | 1.449954961 | 1 | 1.44995496 | 0.023207106 |
| 26435 | 1 | Part_1 | 00:14:41 | -0.003859654 | 0.005333974 | 0.007985765 | 1221.25 | 978.75 | 0 | 0 | 1086.5107 | 869.170375 | 0.236619627 | 1 | 0.23661963 | 0.033749377 |
| 26465 | 1 | Part_1 | 00:14:42 | 0.005367561 | -0.057543601 | NA | NA | NA | NA | NA | 1095.97669 | 813.4090483 | 3.040209815 | 1 | NA | NA |
| 26495 | 1 | Part_1 | 00:14:43 | 0.039733659 | 0.056698576 | 0.052109673 | 1226.25 | 968.75 | 0 | 0 | 1102.916833 | 838.414518 | 3.440841516 | 1 | 3.44084152 | 0.015144456 |
| 26525 | 1 | Part_1 | 00:14:44 | -0.012705604 | -0.020284757 | 0.025052028 | 1226.25 | 968.75 | 0 | 0 | 1121.307233 | 864.699593 | 1.260232833 | 1 | 1.26023283 | 0.019878889 |
| 26555 | 1 | Part_1 | 00:14:45 | -4.48E-05 | 0.002910335 | 0.011983469 | 1226.25 | 968.75 | 0 | 0 | 1118.317737 | 863.0816173 | 0.579750351 | 1 | 0.57975035 | 0.02067005 |
| 26585 | 1 | Part_1 | 00:14:46 | -0.006679378 | -0.005300325 | 0.012247891 | 1226.25 | 968.75 | 0 | 0 | 1117.22093 | 863.160901 | 0.598069746 | 1 | 0.59806975 | 0.020479035 |
| 26615 | 1 | Part_1 | 00:14:47 | -0.013291661 | -0.046146331 | 0.03664279 | 1219.23846 | 964.140528 | 1.147216142 | 0 | 1108.756553 | 855.9186473 | 0.794515312 | 1 | 1.94173145 | 0.018871194 |
| 26645 | 1 | Part_1 | 00:14:48 | -0.009105815 | 0.016212671 | 0.02035037 | 1201.94607 | 958.541971 | 0.741790998 | 0 | 1103.362583 | 856.2738957 | 0.465056293 | 1 | 1.20684729 | 0.016862423 |

Figure 5.10: 2nd Dataset: Audience body and hand movement for each person

### 5.3.3 Self-reported data

In order to test whether (H2) less movement in the audience correlates with more engagement in the performance we relied on the collection of self reported metrics. Due to the difficulty of acquiring any information from the audience members at the end of the performance, video recordings of the performance and the audience were used to collect the metrics. Two online surveys were sent to participants with a range of familiarities to dance. The first survey was used to collect information about the four performances and the second focused on the evaluation of selected audience responses.

#### Survey I: Ranking the performances

The main aim of the performance survey was to identify any differences in the participants' preference among the four performance parts. The survey consisted of five questions and was sent to 22 participants (3 males). The age groups were 18-29 (9 participants), 30-39 (6 participants), 40-49 (1 participant), 50-59 (3 participants) and over 60 (3 participants). Thirteen participants reported they like to watch dance as spectators, while the other 9 were professionally connected to dance. The main question of the survey asked the participants to watch the video recording of each performance part and then put the parts in an order of preference from 1 to 4, where 1 is the most preferable and 4 the least. The order of the performances on the form was different for each participant. The survey can be found in appendix B.

#### Survey II: Assessing Audience Engagement from movement

The audience survey was focused on the participants ability to distinguish if the audience is engaged or not to the performance by watching short selected clips showing the audience. The survey consisted of two sections and was sent to 13 participants (5 males). The age groups were 18-29 (4 participants), 30-39 (4 participants), 40-49 (4 participants) and 50-59 (1 participant). Eight of the participants reported that they like to watch dance as spectators while 5 of them were professionally connected to dance.

The main section of the survey included the audience clips from each performance piece. The clips selection was made based on the upper body movement data. Looking at the upper body movement timeseries of the audience from one of the two cameras, six short clips were selected showing the audience for each of the four performance parts (24 clips in total since there were 4 performance parts). The clips were added to the online survey accompanied by the following question: "On a scale of 0 to 10, how engaged is the audience in the video below? (0 = "Not at all Engaged" and 10 = "Very Engaged"). Under each clip there was a slider with values from 0 to 10. The order of the clips on the form was different for each participant. The survey can be found in appendix B.

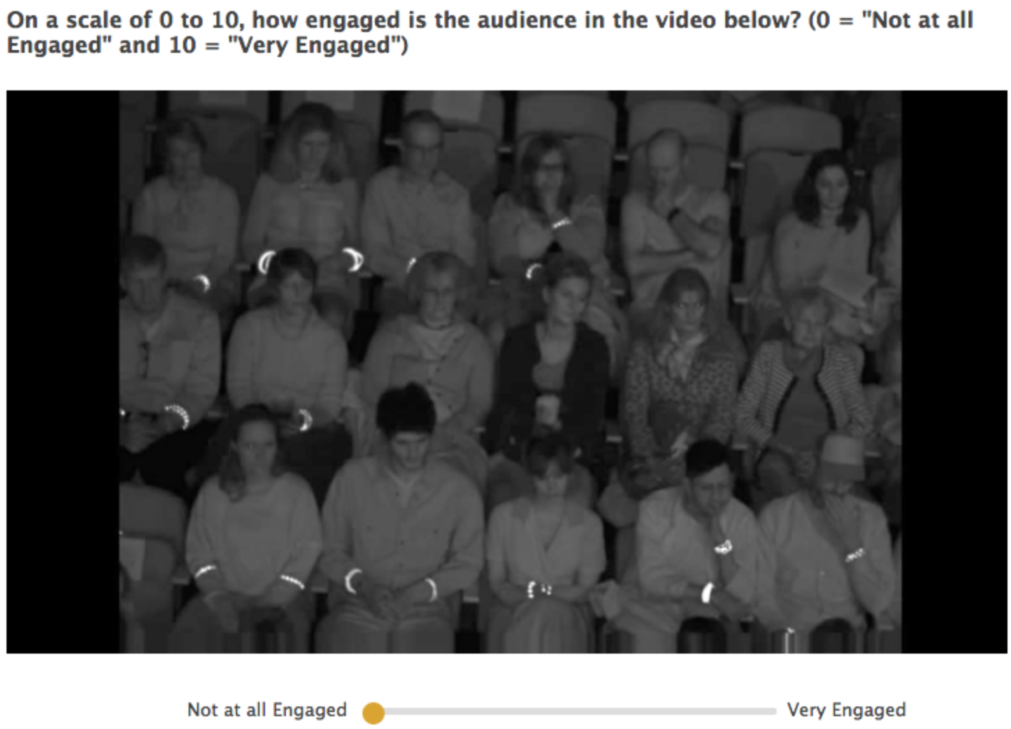


Figure 5.11: Screen shot taken from the audience research questionnaire showing an example of one audience clip

## 5.4 Results

This section presents the results of the second study that took place on the $17^{\text{th}}$ of March 2016 at the The Place theatre in London. Results are reported in three parts. Firstly, the audience responses were examined separately for facial expressions, head/torso and hand movement to test hypothesis 1. Then, the continuous audience responses were compared to the subjective responses collected from the survey, in order to test the key hypothesis that less movement in the audience is associated with moments of audience engagement (H3). Finally, the kinaesthesia hypothesis (H4) was tested by examining audience and performers relationships. Our key findings are summarised at the end of this chapter in the reflective summary section.


Figure 5.12: Audience members from both cameras

### 5.4.1 Audience facial expressions

Facial tracking was applied on one of the two audience video recordings using the SHORE$^{TM}$ software which was able to track for a satisfactory length of time (more than 50% of the duration of the performance) 10 out of 17 faces. The software managed to reliably track the same persons during the whole recording, with a minimum number of persons tracked 5 and maximum at 17. As expected, the lowest numbers of persons tracked were during the interludes when audience members moved more.

The results of this study are similar to the results reported in the first study. The measures of happiness, anger, surprise, and sadness produced by SHORE$^{TM}$ showed substantial inter-correlations. For example, happiness and anger levels are negatively correlated ($r=-0.446$, $p<.001$).

The top two line plots in figure 5.13 show the average levels of displayed "happiness" and "anger" during the performance parts and during the non performance parts (including the applause sections). Both average happiness and anger displayed by the audience were analysed in a Generalised Linear Mixed Model (GLLM) using a Linear Model. For this the performance state (Non-performance or Performance) was defined as a fixed factor and audience member as a random factor. Compared to other distributions such as Gamma and lognormal, gaussian distribution was the one with the best fit according to kolmogorov-smirnov (KS) statistic (see distribution fit in appendices B.5).

The results of the model show a main effect of performance state in audience displayed happiness (Chi-sq=109.22 , $p<0.01$) and on displayed anger (Chi-sq=300.3, $p<0.01$). The GLMM results are reported in tables 5.1 and 5.2 below.

Similar to Study 1, graph 5.13 below shows that people have blank faces during the performance while before and during the applause section there are some animated facial expressions.

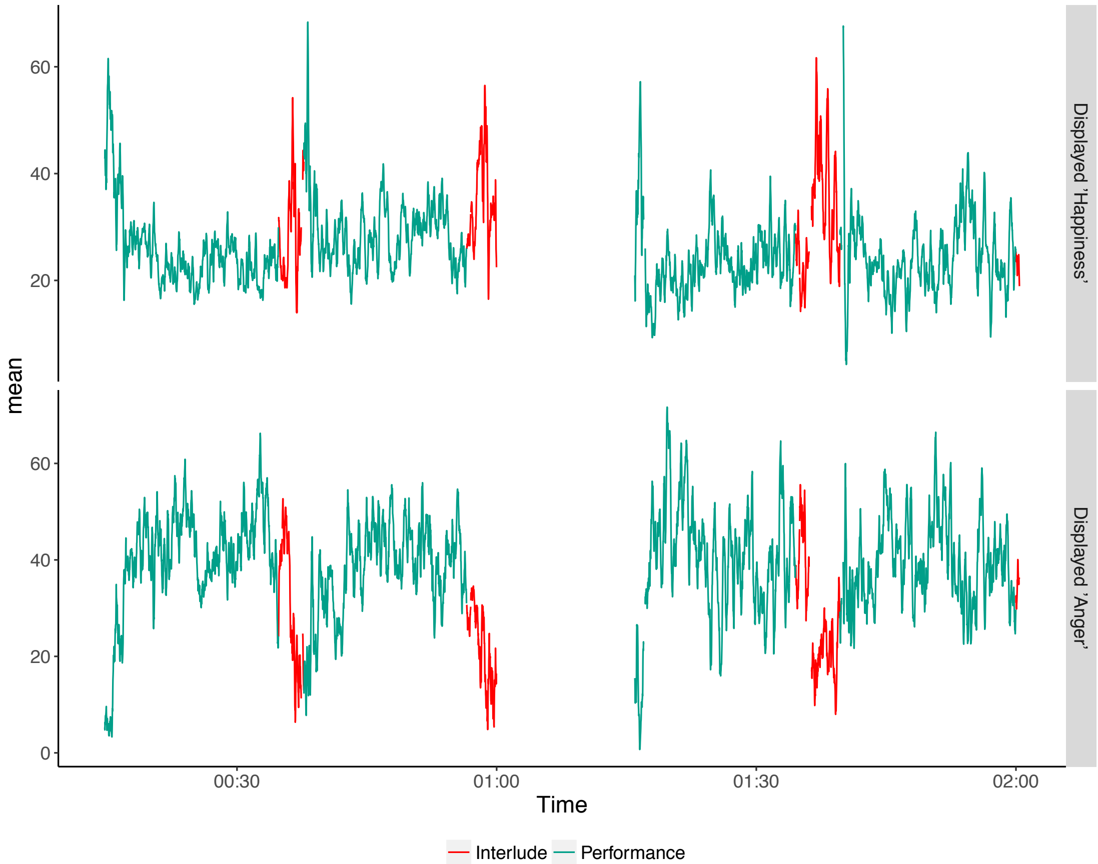


Figure 5.13: Continuous responses during performance and interlude parts averaged across participants. X axis shows the time in hours and Y axis the average values for each measurement

Table 5.1: GLMM model for displayed "happiness" (performance vs non performance)

| | Estimate | Std. Error | df | t value |
|---|---|---|---|---|
| During performance (Happy) | -2.05 | 0.20 | 29255.96 | -10.45 |

Table 5.2: GLMM model for displayed "anger" (performance vs non performance)

| | Estimate | Std. Error | df | t value |
|---|---|---|---|---|
| During performance (Angry) | 5.04 | 0.29 | 29257.89 | 17.33 |

### 5.4.2 Audience head, torso and hands

For the audience upper body movement (head, torso and hands), the data extracted was from 48 audience members (17 males) while for the "hands" and "head and torso" data, the sample size reduced to 38 audience members (11 males) since not all the participants wore the infrared wristband. Figure 5.14 shows the average upper body (head+torso+hands) movement of the audience during the performance parts and the interludes. It is clear from the plot that the movement of the audience members increases during the non performance parts and decreases during the performance parts. This was tested in a GLMM with a lognormal distribution (see distribution fit in appendices B.5). Performance state was defined as a fixed factor and audience member as a random factor. The model shows a main effect of performance state in audience upper body movement (Chi-sq=23818, $p<0.01$). Similar to the blank facial expressions, the audience's body movement seems to become very subtle during the performance parts.

Table 5.3: GLMM model for upper body average velocity (head, torso and hands) (performance vs non performance)

| | Estimate | Std. Error | df | t value |
|---|---|---|---|---|
| During Performance | -0.62 | 0.00 | 308357.00 | -154.33 |

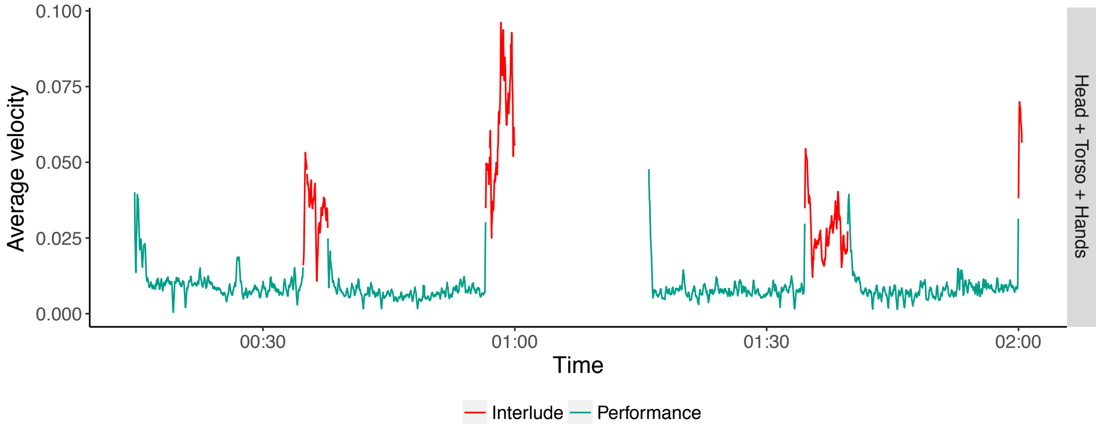


Figure 5.14: Average velocity of head, torso and hands during performance and interlude parts averaged across participants

Figure 5.15 shows the average velocity of the following body parts: 1. Head, torso and hands, 2. Head and torso and 3. Hands during different parts of the performance. It is apparent from the plot that the mobility of the hands is much higher compared to the rest of the body. This was tested only for the parts of the performance using a GLMM with a lognormal distribution (see distribution fit in appendices B.5). The audience body part was defined as a fixed factor and audience member as a random factor. The model shows a main effect of body part on average velocity (Chi-sq=4771.2, $p<0.01$), with the hands average velocity being significantly higher to that of the head and torso. This accepts (H2) and suggests that compared to the other parts of the body, the hands may be the response that is detectable by the dancers.

However it was expected that average head, torso and hands to always be equal or higher to average head and torso. This is not visible in the interlude part of figure 5.15 because of the erratic audience behaviour that affected the efficiency of the tracking during the interludes. Therefore this part will not be included in further analysis.

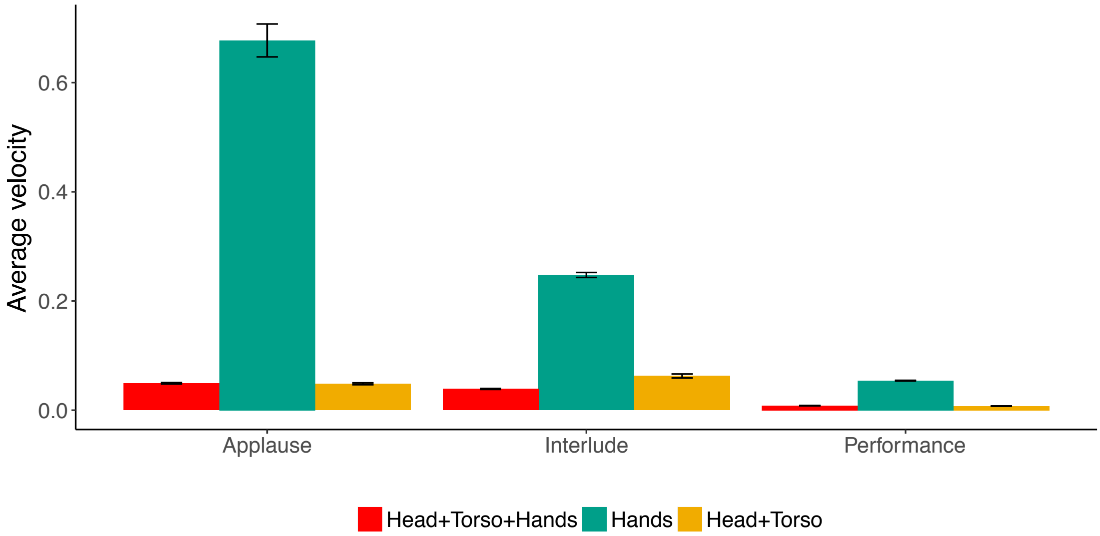


Figure 5.15: Bar plot of audience "head, Torso and hands", "hands" and "head and torso" during applause, interlude and performance parts

Table 5.4: GLMM model for average velocity during the performance (hands vs head and torso)

| | Estimate | Std. Error | df | t value |
|---|---|---|---|---|
| Average velocity of the hands | 1.18 | 0.02 | 228623.00 | 69.07 |

Finally, figures 5.16 and 5.17 show the average velocity of the hands and the total number of hands being on the face for each part of the performance separately. Figure 5.17 shows a general tendency of an increase of the number of hands on to the face as the performance progresses while there is no clear pattern for the average velocity of the hands.

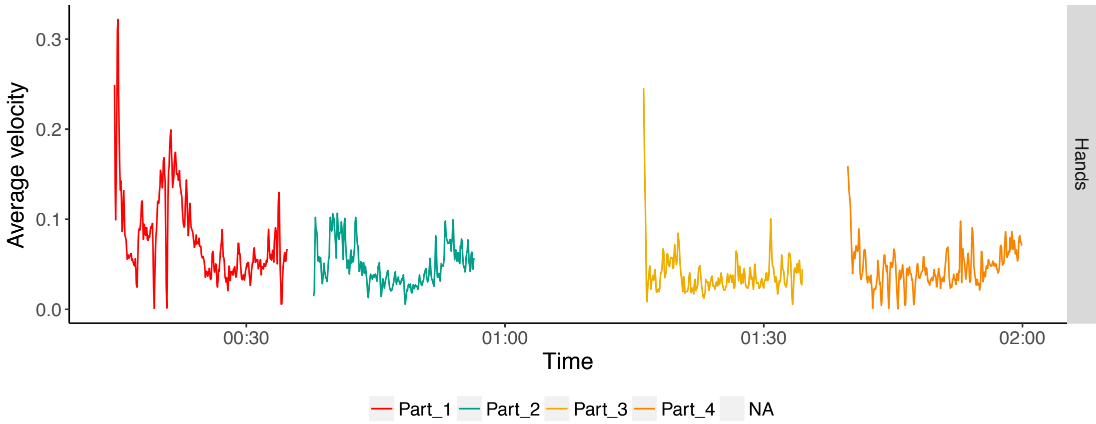


Figure 5.16: Average velocity of the hands during each part of the performance averaged across participants

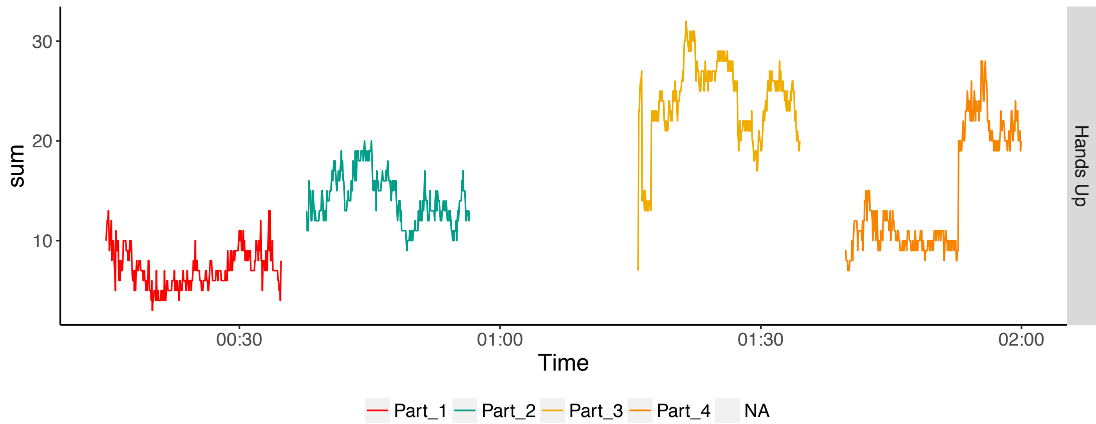


Figure 5.17: Number of hands being up to the face during each part of the performance

### 5.4.3 Left and right hand differences

In this study the hand gesture activities of the audience were not made manually coded but computer vision was used to extract the continuous average velocity of the hands. Based on the results of Study I show that the left hand being used more during the performance compared to the right, this study focused on testing for possible differences between left and right average velocity of the hands. Figure 5.18 shows that the left hand moves more during the performance compared to the right. This was tested in a GLMM using a lognormal distribution (see distribution fit in appendices B.5) with the hand (Left vs right) as fixed factor and audience member as a random factor. The model shows a main effect of the hand on the average velocity of the hands (Chi-sq=333.61 , $p<0.001$) with the average velocity of the left hand being higher compared to the right. However, figure 5.19 shows no difference in the number of times audience members place the left or the right hand on the face.

Table 5.5: GLMM model for average velocity during the performance (left vs right hand)

| | Estimate | Std. Error | df | t value |
|---|---|---|---|---|
| Right Hand average velocity | -0.13 | 0.01 | 230645.00 | -18.26 |

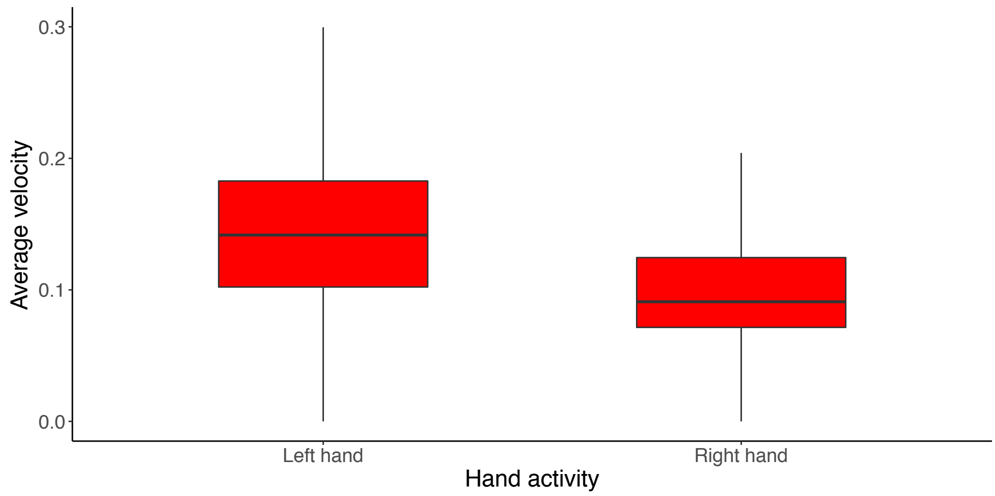

Figure 5.18: Box plot of the average velocity of the right and left hand during the performance

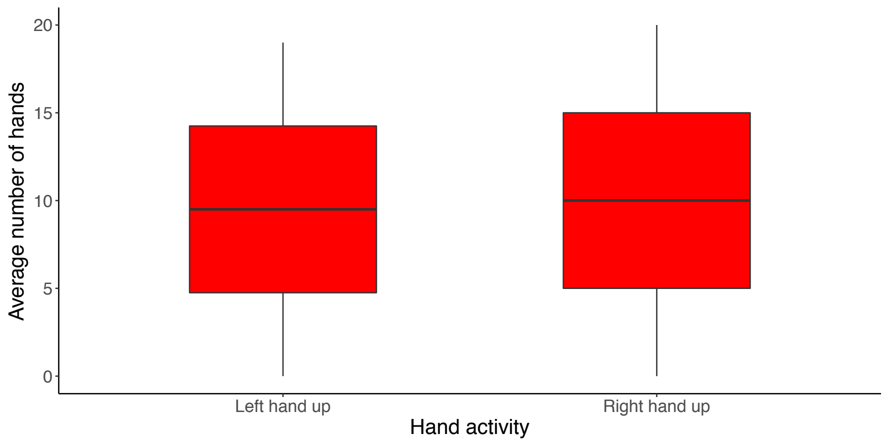

Figure 5.19: Box plot of the average number of the right and left hand being up during the performance

### 5.4.4 Survey I: Ranking the performances

The survey results indicate that the 2nd part of the performance is the most preferred (total ranking=50), with the 3rd part following (total ranking=54) while the 1st (total ranking=57) and 4th (total ranking=59) are the least favourite. A similar pattern exists in the overall movement of the audience with the 2nd (M=0.0071, SD=0.0032) and 3rd

(M=0.0078, SD=0.0042) performances being the ones with less movement while in the 4th (M=0.008, SD=0.004) and 1st (M=0.0101, SD=0.0062) parts the audience tends to move more. A Spearman's rank correlation showed a high correlation between average audience movement and average ranking of the four performances (r=0.8). However the result is not statistically significant (p=0.33) mainly due to the small sample size of the performances (4).

### 5.4.5 Survey II: Ranking the audience

A GLMM with a linear model was used (see distribution fit in appendices B.5) to test for any significant difference in the engagement scores for high and low movement clips. To carry out this, the movement state (moving versus non-moving) and connection of participants to dance (performers vs non performers) were tested as fixed factors and participant and number of times they attended a dance performance in a year (0-4) as random factors. The results show a main effect of the movement state on the engagement scores (Chi-sq=95, p<0.01), with participants ranked as more engaged the audience clips where the audience was moving less. The model does not show any effect for participants connection to dance (Chi-sq=0.22, p=0.63) on the engagement scores.

Overall, this finding suggests that participants reported that audience members were more engaged to the performance when they were moving less.

Table 5.6: GLMM model for engagement levels

| | Estimate | Std. Error | df | t value |
|---|---|---|---|---|
| Movement state (Moving) | 1.02 | 0.11 | 298.00 | 9.73 |
| Connection to dance (Performer) | -0.13 | 0.29 | 11.00 | -0.44 |

### 5.4.6 Audience - Dancers Interaction

Since the final hypothesis focuses on kinaesthesia (H3), it was considered appropriate to use the granger causality (GC) analysis to test if the audience movement could be predicted from the movement of the dancers. Each part of the performance was examined separately and for lags between -9 and +9 seconds and assessed granger causal relationships at temporal delays between 1 and 9 seconds. Positive lags indicate dancers movement predicting audience movement while negative lags indicate the opposite (Figure 5.20).

GC was tested separately between audience hand movement and dancers movements and between audience head and torso movement and dancers movements. The relationship between the audience and the dancers is considered predictive only if it is unidirectional (see section 3.6.1 for more details). To ensure stationarity, all timeseries were differenced by subtracting consecutive sample points from each other prior to applying GC.

This was tested both for matching responses (e.g responses from the same performance part, audience body movement from Part2 with dancers movement from Part2) and for mismatching responses (e.g responses from the different performance parts, audience body movement from Part2 with dancers movement from Part4). Randomly mismatching responses should cancel significant relationships between dancers and audiences that exist for responses that are derived from the same performance.

Overall, the GC results show that the dancers movements do not systematically predict audience movement. This finding conflicts with hypothesis 3. However, the results show a systematic but surprising prediction in the opposite direction. Specifically, in Parts 2 and 3 the dancers movement is predicted by the audience movement. The results are reported separately for each performance part as seen in the plots in figure 5.20).

There is no statistically significant GC relationships between either hand or head and torso movement and dancers movement for Part 1 (p at all lags $>$ .05). For Part 2, audience hand movement predicts dancers movement at a lag order of 3 sec, $F(3,1120)=2.7110$, $p=0.04$, 5 sec $F(5,1116)=2.6807$, $p=0.02$ and 9 sec $F(9,1108)=2.3561$, $p=0.01$. Similarly in Part 2 audience head and torso movement predicts dancers movement at a lag order of 3 sec $F(3,1108)=1.9223$, $p=0.04$. For part 3, audience head and torso movement predicts dancers movement at a lag order of 1 sec $F(1,1119)=5.0373$, $p=0.02$ while part 4 shows a bidirectional relationship. Audience hand movement predicts dancers movement at a 5-second lag order $F(5,1208)=2.5377$, $p=0.02$ but also dancers movement predicts audience hand movement at a lag order of 7 sec $F(7,1204)=2.087$, $p=0.04$.

This suggests that in part 4 there should be an exogenous variable such as the soundtrack of the performance (see more details is section 3.6.1) which influences both audience and dancers.

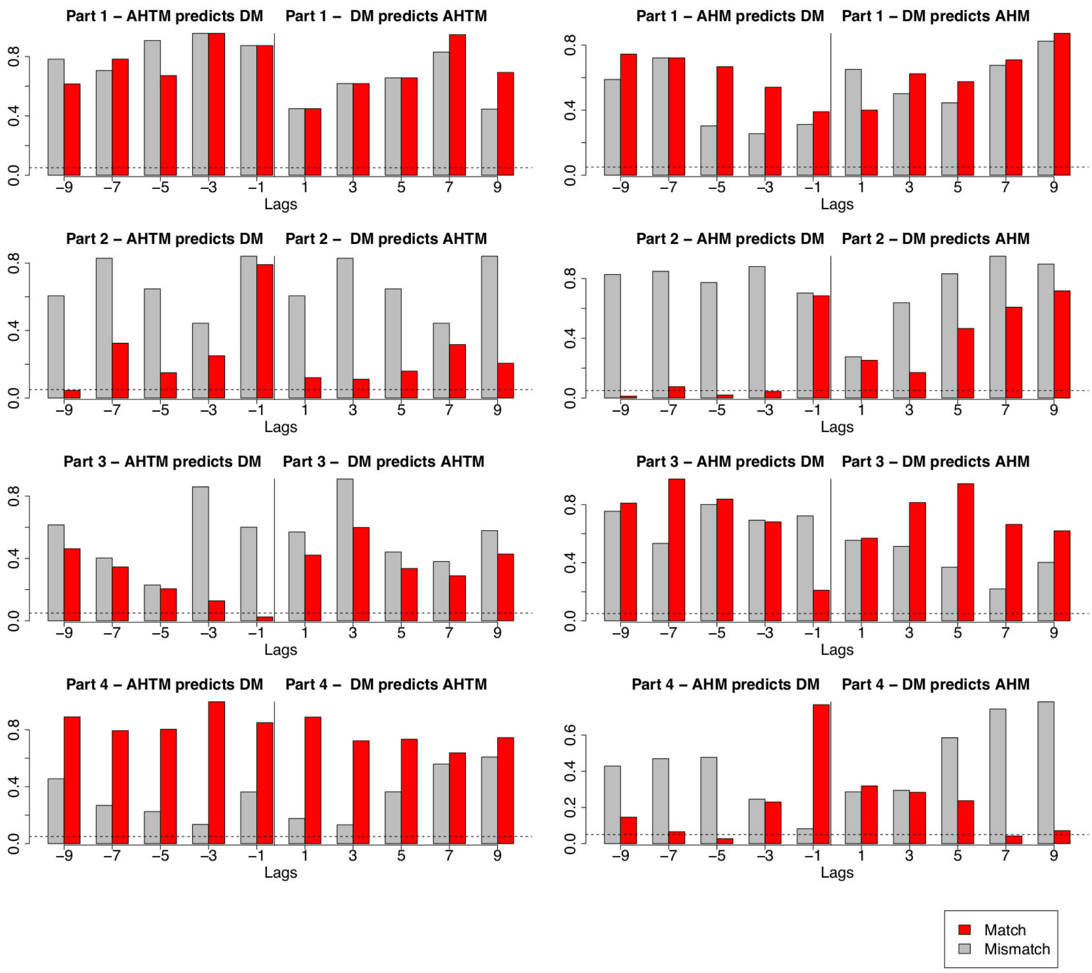


Figure 5.20: GC for audience head and torso movement (AHTM) and dancers movement (DM) in each performance part (plots in left column), GC for audience hand movement (AHM) and dancers movement (DM) in each performance part (plots in right column). The x axis indicates the lag order and the y axis the p values. The dashed line indicates a significance level of $p \leq .05$

GC analysis was also used to test for any relationship between the audio power of the performance and audience hand and body responses. As seen in the figure 5.21 below, the GC results do not show any statistically significant influence between hand or head and torso movement and audio power of the performance for Parts 2 and 3 (p at all lags $> .05$). The results show that in Part 1 audio power predicts audience hand movement at all lags ($F(1,1175)=8.1248$ $p=0.004$, $F(3,4.1057)$ $p=0.006$, $F(5,3.6370)$ $p=0.002$,$F(7,2.7968)$ $p<.01$, $F(9,2.4656)$) while surprisingly for lag order of 1, 3 and 7 sec there is a bidirectional influence ($F(1,1175)=5.5061$ $p=0.01$, $F(3,1171)=2.8783$ $p=0.03$, $F(7,1163)=5.1810$ $p=0.01$). In addition, the results show an unexpected strong prediction of audio power from the hand movement of the audience ($F(1,1175)=12.9923$, $p<.01$, $F(3,1171)=6.0057$,$p<.01$, $F(5,1167)=4.2107$ $p<.01$, $F(7,1163)=5.1810$ $p<.01$, $F(9,1159)=3.1967$ $p<.01$).

Finally, in part 4 audio power of the performance influences the hand movement of the audience at the lag order of 5sec (F(5,1207)=2.1607, p=0.05).

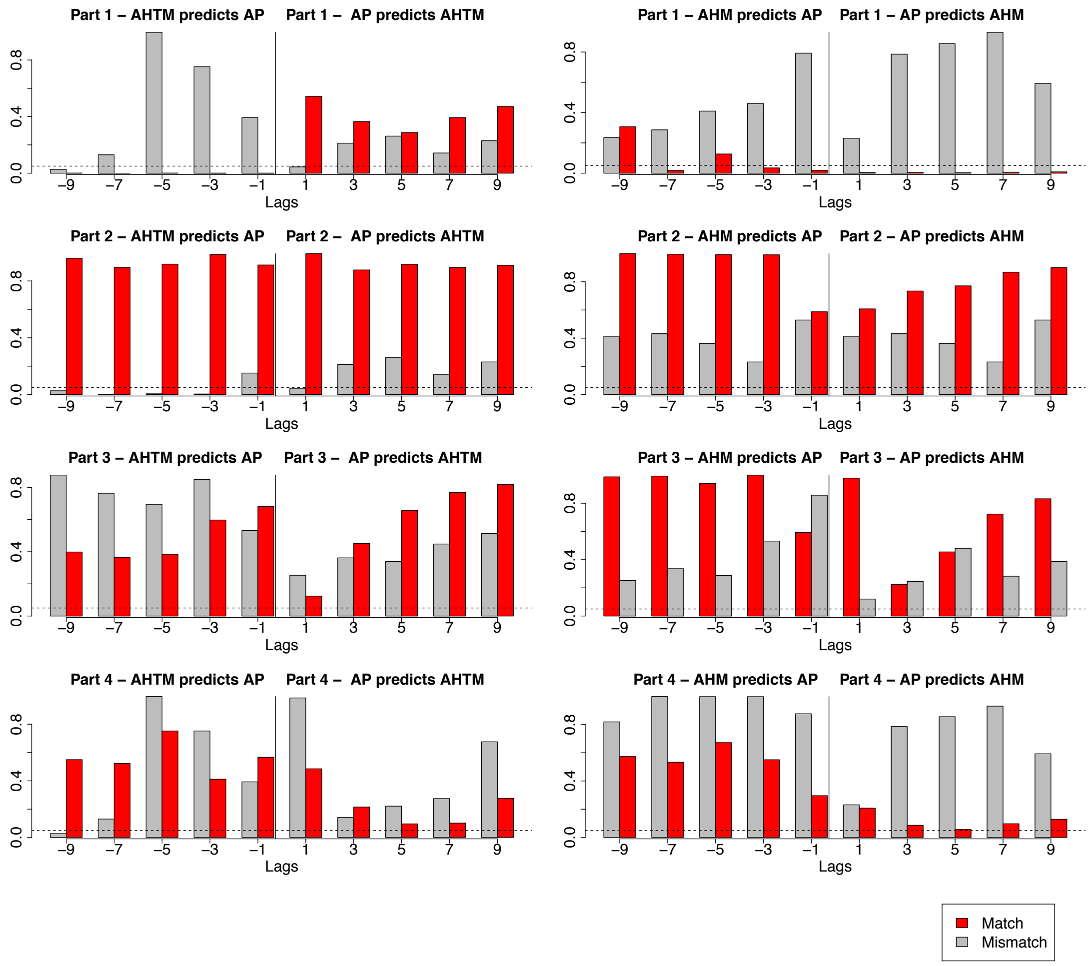


Figure 5.21: GC for audience head and torso movement (AHTM) and audio power (AP) in each performance part (plots in left column), GC for audience hand movement (AHM) and audio power (AP) in each performance part (plots in right column). The x axis indicates the lag order and the y axis the p values. The dashed line indicates a significance level of p $\leq$ .05

## 5.5 Reflective summary

This chapter presents the second study of the thesis which had as its main objective the closer examination of audience hand behaviour, as well as to test to test for any possible connection between audience movement and engagement. This study followed a similar methodological approach to Study I apart from introducing a new automatic method of hand movement tracking and using self-reported surveys as a supplementary material to test specific hypotheses.

The results of the study provide evidence that there is a relationship between audience body movement and engagement, which raises a number of interesting questions. The main finding is that according to 13 external "judges" deciding on the engagement levels of 24 audience clips, participants reported highest engagement levels in the clips where audiences move least. Moreover, it appears that the judges may have been responding more to hand movements than head and body movement as hands move significantly more than the rest of the body. This suggests that audience hand movement is the part of the body that is both frequently and potentially detectable to the dancers. This finding is consistent with the observations from Galton (1885) and Pasquier (2015) mentioned in Chapter 2, of engagement for audiences in lectures and theatres. The focus on the hands suggests that people become restless and this leads to more spontaneous self-touching gestures. This is compatible with the literature that claims that such gestures relate more to audience boredom or nervousness (Theodorou and Healey, 2017; Mahmoud et al., 2011). However, even though head movements are less obvious, it is possible that they may also be a significant component of audience response. This is something that cannot be resolved by using the current analysis, however the movement of the head has a strong connection with that of the torso while hands have more degrees of freedom to move independently from the rest of the body. Therefore, measuring the torso without the hands might be a good approximation of the movement of the head separately.

Another observation from Study I that is also supported here is that overall audiences move very little and have predominantly expressionless faces during the actual performance parts. This is in clear contrast to the animated facial expressions and body movements that are apparent during intervals. The decrease of body movement is something that was expected since audiences are physically very restricted during a performance as they are supposed to be sitting quietly on a chair observing and making sure they don't annoy the performers or the rest of the audience. However, the fact that audiences have predominantly blank faces during the performance was not expected. This can be interpreted as a sign of concentration connected to people's senses that they are not actively socially engaged during the performance. Overall, it is apparent that the facial expressions and hand gestures of the audience examined here are different from those involved in focused social interaction. In face-to-face interactions, social communication guides the non-verbal interaction (McNeill, 2008). During a conversation objects in the surrounding environment and spoken concepts lead the gestures and the facial expressions but it is apparent that in the case of an audience in a performance, social displays are greatly reduced. Therefore, hand to face gestures and facial expressions may be more representative of the cognitive-affective states that accompany the audience during the performance.

In addition, even though in Study I the results showed that the average velocity of the audience was decreasing during the performance while there was an increase in the number of audience hands on face, the results of this study did not show any clear pattern of average hand velocity during each part of the performance while overall there was an increase in the number of hands on face. This might be due to the shorter length of these dance pieces (15 minutes) compared to the piece in Study I (37 minutes without a break) which does not allow enough time for the audience to reach a moment of boredom.

With regards to left and right hand behavior the results of this study show no significant differences between the use of the right and the left hand but show a significant difference in the average velocity of the hands with the left hand moving faster than the right. A possible interpretation of this might be that audiences use their left hand to perform more self touching gestures such as scratching while the right hand is used more for more static gestures such as holding their head. However, as mentioned in the previous study some caution is required in interpreting this result since there is no information on audiences handedness.

In terms of audience and dancers live communication, granger causality analysis did not show any systematic influence of audience movement from the movement on the stage. However, an unexpected finding that came our from this analysis was the influence that audience movement has on the movement of the dancers as well as the the relationship between audio power of the performance and audience movement. According to Dean and Bailes (2010) research on real time perception of music, listeners cannot influence acoustic parameters and these are appropriately taken to be exogenous variables while the perceptual parameters are endogenous. Is this supported also in dance? Is there a way for audiences to influence dancers movement? One interpretation of this might be that the choreography builds up specific expectations which may lead to this influence or that the timing of the choreography adjusts slightly depending on the audience. However the latter may be unlikely in cases similar to the one we have here where the soundrack was recorded and not live. This is something that needs further investigation that focuses more on the aesthetic elements of a dance performance. A more detailed discussion on this is given in Chapter 7 of this thesis.

Finally, it's important to note here that the use of self-reported surveys in this context raises concern. As mentioned in section 4.3, the results of the survey that came out from the subjective responses of the performance parts show no significant differences in the preference levels among the four performance parts. This finding suggests that looking at the overall metrics of one performance compared to the other is not an efficient way to identify moments of high or low engagement in an audience. The reasons for this might be that moments of engagement or boredom might happen during very short moments of a performance and overall metrics would not be able to identify them. This shows that to be able to identify moments of engagement during a performance the focus needs to be on the momentary engagement of the audience rather than on the judgements of a dance piece as a whole. This is a challenging part that needs to be explored in future work by showing people shorter videos from different parts of a performance instead of complete performances. However, one of the important criticisms of quantitative approaches to dance research is that dance unfolds in time, making the collection of data too simplistic if an entire dance piece can be reduced to a number.

# Chapter 6

# Audience responses part III: Identifying moments of engagement based on movement

## 6.1 Introduction

This chapter presents the final study of the research, which was focused on further clarifying and formalising the results of the previous studies. The hypotheses generated are thus similar to the previous two chapters but they are examined from a different angle and using a more controlled methodological approach. The first result that is examined more closely is that hands in particular have a significant role to play in understanding how the audience reacts to the performance. This is evident through their increase of movement during the performance and the unexpectedly contrasting behaviours between the left and right hands as observed in chapters 4 and 5. In this case, a more hi-tech method was used (wristbands with accelerometers) which also allowed for the collection of more detailed and more accurate measurements. Another result more closely explored is the one found in the second study, that there is an association of audience engagement with stillness. For this personalised engagements were captured using questionnaires and examined against movement data provided by the wristbands. Finally, the relationship between the movements of the audience and the dancers is re-examined, although the previous studies didn't find it to be systematic. Thus, the hypothesis examined in this chapter are as follows:

***Hypothesis 1 (H1):*** *There are significant differences between the use of the right and left hand during the performance and are depended on handedness.*

***Hypothesis 2 (H2):*** *Movement and engagement are inversely correlated.*

***Hypothesis 3 (H3):*** *Audience movement can be predicted from dancers movement.*

## 6.2 Context: 8 Minutes - A contemporary dance performance by Alexander Whitley

The data examined for this study was collected for audience and dancers during the contemporary dance performance "8 minutes" that took place at Sadler's Wells theatre on the 27th of June 2017. "8 minutes" is a contemporary dance performance directed by Alexander Whitley in collaboration with the composer Daniel Wohl and the video artist Tal Rosner. The performance is one hour long and has a cast of 8 dancers. For this piece Alexander Whitley takes inspiration from the images and the data produced by solar science research in collaboration with scientists from STFC RAL Space (Lead scientist: Hugh Mortimer). The piece incorporated a high definition projection wall behind the dancers and electroacoustic music to accompany the performance (see figure 6.1). According to Whitley, the performance is divided into four main parts each of which was further divided in subparts as follows: ***Space:*** *Shapes, Rebound, Formless, Orbit* ***Earth:*** *Ships, Melt, Primal* ***Transcendence:*** *Surrender, Corpus, Sunray* ***Death:*** *8 Minutes*

Figure 6.1: "8 Minutes"- A contemporary dance performance by Alexander Whitley

## 6.3 Materials and Methods

The study used a two-tier approach that combined continuous measures of movement and self-reported data sources. The methodological approach was different to the previous two studies because of the more targeted hypotheses but also due to the availability of new sensing equipment: 28 wearable devices used to measure hand movement (Empatica E4). The experimental design of the study was divided into three main parts (see figure 6.7). In the first part participants were recruited using a pre-performance survey. In the second part data was collected during the performance while in the final part two post performance surveys were sent to each participant.

### 6.3.1 Data capture: Equipment and technical specifications

Empatica E4 is a wearable device embedded with diverse sensors which is able to collect several types of data simultaneously. The wristband contains a PPG sensor from which heart rate variability can be derived, a 3-axis accelerometer to capture motion-based activity, a GSR sensor that measures the constantly fluctuating changes in certain electrical properties of the skin, an infrared thermopile that reads peripheral skin temperature and an internal real-time clock with a temporal resolution of 0.2 seconds in streaming mode (Garbarino et al., 2014). The wristband has a battery life of 20+ hours and is comfortable to wear without emitting light during data collection, which is one of the reasons it was chosen for this study.

Figure 6.2: E4 Wristband made by Empatica

Given that the main focus of this research was on the collection of motion data, only the 3-axis accelerometer data was examined. The accelerometer is configured with a sample frequency of 32Hz and measures 3 axes, X, Y and Z. Its default range is 2g although ranges of 4g or 8g are selectable with custom firmware. The signal resolution is 8 bits of the selected range, from -127 to 128. For this study, the accelerometers were configured with a range from -8g to 8g which is more than enough to capture any sudden movements of the hands.

The wristband can operate in streaming mode for real-time data processing using a Bluetooth 4.0 (Bluetooth Low Energy - BLE) interface or in-memory recording mode using its internal flash memory. In real-time streaming, the E4 wristband can connect via the Empatica API to a mobile terminal (iOS, or Android platform) or to a computer via BLE. An application for data acquisition is available from the mobile online stores to collect data in real time. At the end of the acquisition, sessions are uploaded to the Empatica server (see figure 6.4). In this study the in-memory recording mode was used as no real time analysis was needed. For this recording mode, data is stored into the internal flash memory of the wristband and, at the end of the acquisition session, the wristband needs to be connected to a computer (PC or mac) via a USB in order to upload data to the Empatica cloud server through the Empatica Manager.

The Empatica Manager is a desktop memory sync program that performs this operation automatically as soon as the user has logged in and connected a sensor. Data upload is secure and does not include personally identifying information, allowing the system to satisfy both USA and EU HIPPA requirements


Figure 6.3: E4 Wristband connection circle

The raw data then becomes available for download as comma-separated (csv) files through the Empatica Connect web platform. This web platform (see figure 6.4) allows for access and review of all the sessions recorded with the E4 wristbands associated to an account 6.4). Data from each session can be visualised (see figure 6.4) or downloaded in timestamped CSV format, making it easy to import into any data analysis tools.

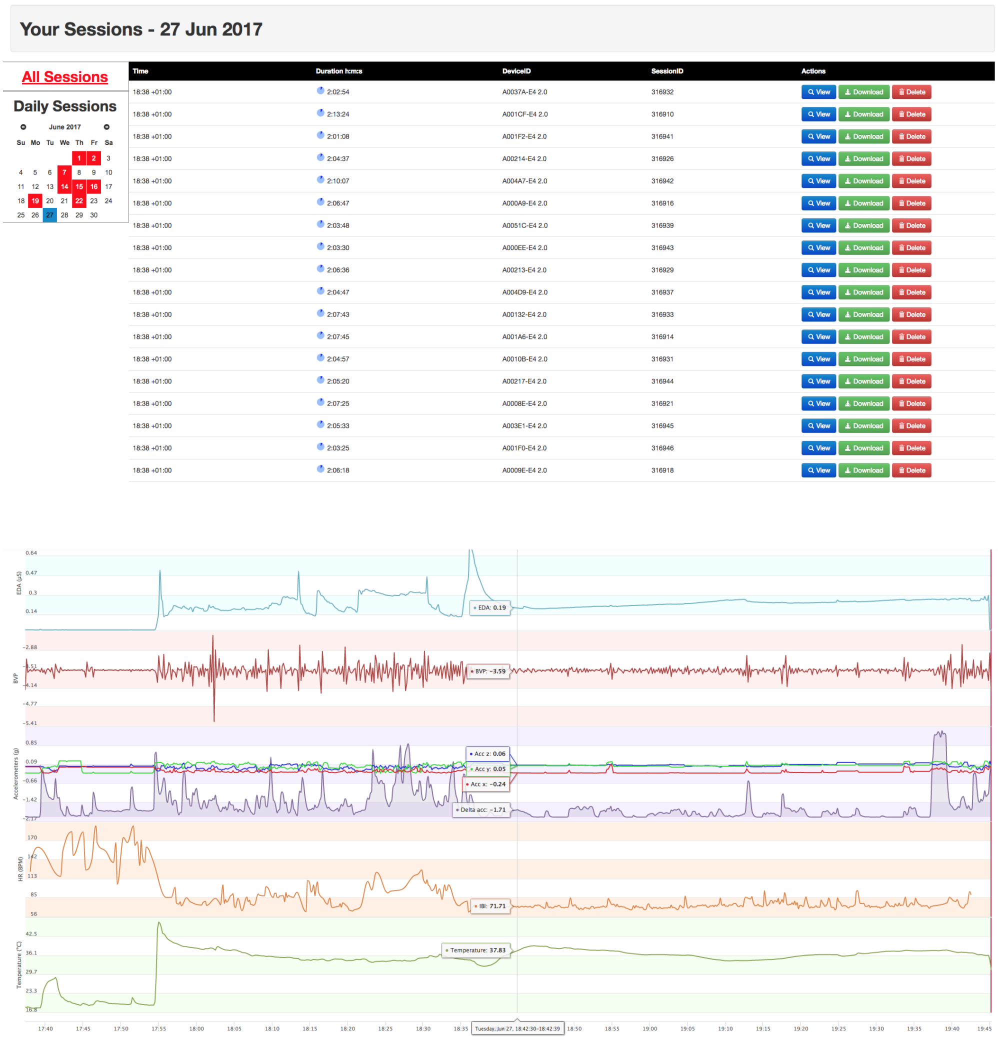


Figure 6.4: Empatica connect Interface and data visualisation tool

### 6.3.2 Participants

A total number of 28 wristbands were available which were distributed amongst 28 participants (11 males and 17 females) that took part in the study and attended the performance. The participants were recruited through an online survey that was distributed using a number of electronic mail lists. The advertisement of the study was written as follows:

"Do you like dance? If yes, take a break and take part in our study! Free Tickets to attend the premier of a new dance performance by Alexander Whitley Dance Company that will take place at Sadler's Wells Theatre on the 27th of June. You can find information about the performance in the following link: http://www.sadlerswells.com/whats-on/2017/alexander-whitley-dance-company-8-minutes/ If you are interested please use the link below to register. Once you are selected for the study, you will receive an email with your ticket and more information about the study! https://docs.google.com/forms/

d/e/1FAIpQLSfM$_2DhunzIaq0X0oAAryRLEeEV78ci15KEtOrcXgV9rT3d1g/view$
$form?c = 0w = 1$”

The selection of participants was based on their familiarity with dance as we were more interested in participants that enjoy watching such performances. The participants were divided into four age groups: 18-29 (10 participants), 30-39 (15 participants), 40-49 (1 participant) and 50-59 (2 participants). In terms of the participants' familiarity with dance, 22 of them reported that they like to watch dance as spectators while 6 of them were professionally related to the field. Half of the participants (14) also indicated that they attend dance performances more than 4 times a year and only 2 of them have never been to a dance performance in the past.

### 6.3.3 Procedure

The dance performance and study took place at the Sadler's Wells theatre in London on the 27th of June 2017. Sadler's Wells (see figure 6.5) is one of the world's leading performing arts venue based in London. It consists of two performance spaces: a 1,500 seat main auditorium and the Lilian Baylis Studio. The study was confined to the stalls area of the main auditorium. In an ideal scenario the seats of the participants would be randomly distributed through the stalls and, to avoid group contagion, not next to each other. However, this was not possible due to seat availability. The tickets provided by the theatre were randomly distributed in the stalls area but they were clustered in groups of 2,3 or 4 (see theatre plan on figure 6.7).

Due to the low number of wristbands, a between subjects design was followed. On the day of the performance each participant was provided with one wristband. According to hypothesis (H1) which aims to test right and left hand differences, the placement of the wristbands was decided to be on the dominant hand for 14 participants and on the non-dominant hand for the rest. This let us test both whether there is hand asymmetry (diiferent behaviour of left vs right hand) when participants watch the performance but also if it depends on whether people wore the wristband on the dominant or the non-dominant hand. Prior to the performance the sensors were calibrated and synchronised and the participants advised to move freely without thinking about the wristbands. In order to synchronise the acceleration data with the video of the performance, the event marking button of the wristband was used. At the beginning of the performance the marking button was pressed on camera and logged a timestamp in the session archive. This event mark was used later to align the acceleration data with the video.

After the performance each participant was asked to fill in two online surveys. The first survey included general questions about the performance and was sent to the participants directly a few hours after the event. The second survey was used to specifically test hypothesis 2 (H2) and was customised for each participant separately (see details in section 6.3.6 below). Given that personal data of the audience members was to be included, privacy became an issue in this study.

The study was certified with an ethical approval from the Ethics Committee of Queen Mary University of London (Ethical approval reference number: QMERC1432a) and each participant signed a consent form before attending the performance (find in Appendix C).

Figure 6.5: Sadler's Wells theatre

### 6.3.4 Continuous Dataset: Audience and dancers

The main data type collected from the wristbands and subsequently used in the analysis was acceleration (ACC) changes over time with a sample rate of 32fps. The first step of the signal processing was to match the timestamp for each frame to the equivalent time in the video of the performance. The E4 stores time in the Unix time format which is a count of seconds from 01 JAN 1970 at 00:00:00 UTC. This was used as the origin to define the starting time for each timeseries. The timeseries of the audience were then aligned with the video of the performance.

For analytic purposes the raw data was converted to actual G-units by multiplying them with xg = x* 8/128 (a value of x = 16 is in practice 1g). In order for all the timeseries to be at the same baseline z-score standardisation was applied. Standardisation is critical in order to compare data across a big number of subjects whose individual measurements vary. The magnitude of acceleration was then calculated from the 3-axis acceleration data, by taking the square root of the sum of squared x, y and z values, leaving a single timeseries vector for each participant. For an economy of data and to be able to synchronise the audience dataset with that of the dancers the set was downsampled to 1Hz. As mentioned before, this decision was made given earlier studies (Schubert, 2004), which indicated that real-time perceptual responses generally take at least 1 to 5 seconds for full registration. For each participant, we calculated the magnitude of the acceleration over a rolling window of 1Hz and then averaged across all 28 participants.

The resulting timeseries represented the average acceleration for all participants, with greater values indicating increases of movement intensity and lower values indicating a decrease and zero values no movement.

In addition to the testing of the continuous audience responses, we wanted to also test for possible relationships between audiences and performers as carried out in the previous studies. Since video projection and sound were important elements of this piece, the video recording of the performance was used to extract the average velocity of the dancers and the projection as well as the audio energy. Similarly to the previous studies (see Chapters 3,4), an optical flow algorithm was used to calculate the average velocity on stage separated from that of the dancers and that of the video projection. In order to separate dancers from projection movement the video of the performance was splitted in two sections (see figure 6.6) and the optical flow algorithm was applied in each section separately. The two images below show optical flow applied on two different scenes of the performance. In the image on the left the movement of the dancers is higher compared to that of the projection while the image on the right shows the opposite. This was the most accurate way to distinguish between the visual change of the projection and the movement of the dancers. The video sample rate was 24Hz but it was donwnsampled to 1Hz for an accurate synchronisation with the audience dataset. As in the second study presented in Chapter 5, the power of the soundtrack (the audio dataset) was averaged to every second, calculated using the miraudio toolbox for Matlab (Lartillot and Toiviainen, 2007) and an operator called Root Mean Square (RMS).

The final continuous dataset that included data both from the audience and the performance consisted of the following columns: Audience.Avg.Acceleration, Dancers.Avg. Velocity, Projection.Avg.Velocity, Audio.Power.

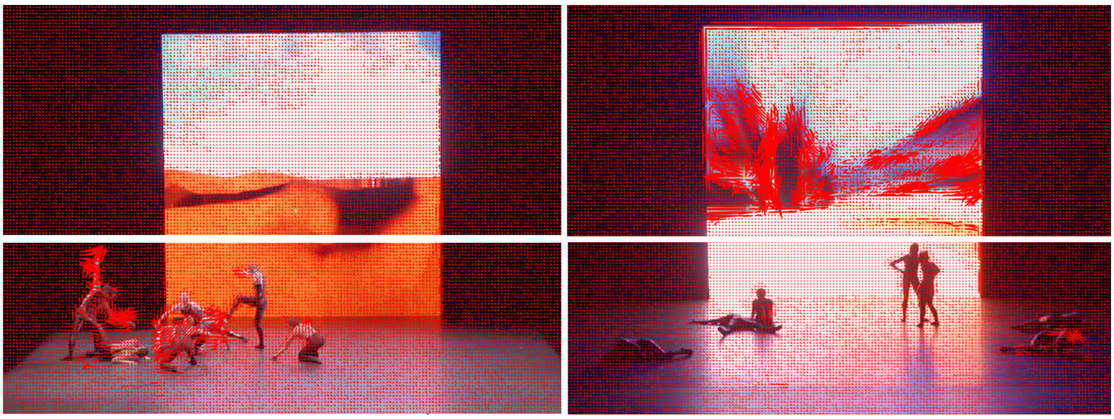

Figure 6.6: Optical flow calculating the average velocity of video projection (top images) and dancers (bottom images) separately. Increased average velocity was indicated with longer red lines in the image

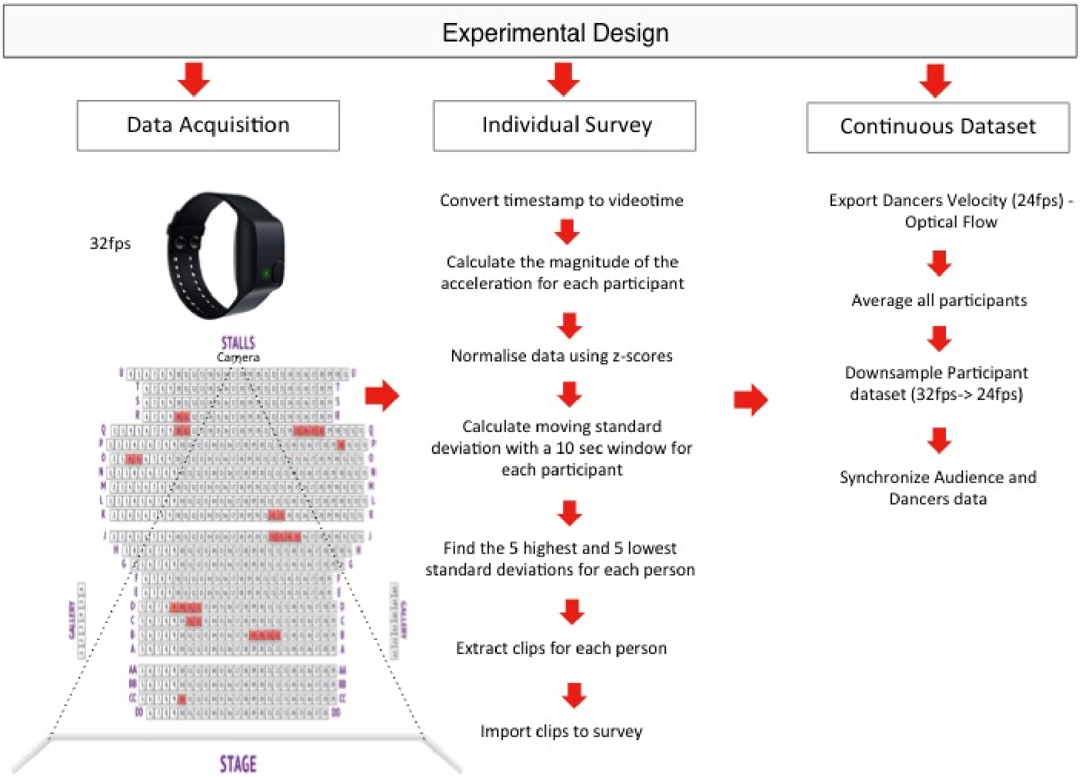


Figure 6.7: Data collection and data processing pipeline

### 6.3.5 Survey I: General evaluation of the piece

At the end of the performance, all 28 participants (17 females, 11 males) were asked to complete an exit survey. The main aim of the survey was to get the participants' overall understanding of the performance as a whole. The survey consisted of 13 questions: eight agree/disagree questions and 3 open-ended questions. The first 8 questions of the survey included general statements about the performance as a whole while the three questions at the end were more focused to identify specific elements or moments that participants liked or disliked. The questionnaire items are listed below. In the first 8 questions, the qualifiers of the response categories were as follows:

*Strongly Agree - Agree - Neither Agree or Disagree - Disagree - Strongly Disagree*

For the sake of clarity these qualifiers were repeatedly stated below the corresponding tick boxes for each individual questionnaire item. The original form is included in Appendix C.

1. I was absorbed by what was happening in the performance

2. I was easily distracted while watching the performance

3. The performance didn't really hold my attention

4. I felt immersed in the sights and sounds of the performance
5. I felt tired and uninterested
6. I hardly noticed time passing during the session
7. I enjoyed watching the performance
8. I found the performance boring

The 3 open ended questions were the following:

1. Were there specific parts or elements of the performance that you liked the most? If yes, can you describe your favourite parts/elements in a few words?
2. Were there specific parts of the performance that made you feel bored or elements that you disliked? If yes, can you describe your least favourite parts/elements in a few words?
3. Please use the space below to leave any other comments you may have about the performance or your experience during it.

### 6.3.6 Survey II: Identifying participants' engagement moments

The purpose of the second survey was mainly to test hypothesis 2 (H2), that is whether the participants move less during the performance parts that they liked the most. This was done in order to validate the underlying relationship between the movement of the audience and the level of engagement identified in the previous studies. For this, a customised online survey was created to evaluate each participants' personal experience during the performance. The content of the survey was different for each participant and depended on their activity during the performance.

Based on the acceleration data of each participant, the five highest and five lowest moments were calculated. The 10 moments were then mapped to the corresponding parts in the performance and used to extract the relevant sections from the video. The 10 video clips were then imported to an online survey and were sent to each participant separately two weeks after the day of the performance. The final set included 280 clips, 10 for each of the 28 participants. After a few informal tests, the duration for each video clip was set at 10 seconds. This was considered enough time for people to remember the scene and decide how much they enjoyed it when they watched it.

At present, almost all commercially used accelerometers downsample their raw data by averaging the magnitude of the acceleration, which is an aggregate measure of amount and intensity of activity over a specific time period (Vähä-Ypyä et al., 2015). However, since in this study we are only interested to distinguish between moments of high and low movement in the audience, averaging the magnitude of acceleration might not be accurate enough as a metric. This is to avoid cancelling out moments of extreme fluctuations of acceleration and deceleration moments which would equate them with moments where no acceleration occurs. Therefore, a measure of dispersion was chosen as a better metric. According to (Vähä-Ypyä et al., 2015) among different traits, the mean amplitude deviation (MAD) was considered the best trait for an accurate classification of movement intensity. MAD is a measure of dispersion similar to standard deviation (SD) but less influenced by extreme values. Based on this, the analysis was carried out using MAD as the primary measurement. To find the movement of each participant during the 10 seconds, MAD was applied over a 10 second rolling window.

For an accurate identification of the five lowest and five highest moments of each participant, the minimum and maximum values from the distribution which were at least five seconds away from each other were selected. More specifically, to select the minima, the algorithm initially finds and stores the minimum value of the whole timeseries subsequently removes it from the distribution along all values five seconds before and five seconds after that moment. In this way the algorithm avoids selecting moments that are close together, a likely possibility given that a person can be still for a while keeping thus the measured acceleration continuously low. The algorithm then selects the next available minimum value and so on. The same process is carried out for the maxima. However, the algorithm can still select two high/low moments that fall in the same scene, although this is more likely to happen for the minima given that people tend to move little during the performance. In order to avoid this and get a bigger range of comparison among parts more moments were extracted (20 maxima and 20 minima) and reduced to five manually for each category depending on their position on the timeline.

The algorithm did not take into account that the acceleration measurements were highly skewed towards zero and that differences between periods of movement and non movement were very small and thus, as a result, some minima could also be considered as maxima. To avoid this the clips were reclassified using two different thresholds. Firstly, the mean of the MAD of each participant timeseries was used as a threshold to divide the moving and non moving clips while zero MAD was used as the second threshold. MAD equals to zero occurs when a person is in absolute stillness.

This new classification allowed for different number of clips in each category (moving and non moving), but since the analysis focused on averages of moving and non moving clips this should not affect the results. An example of the three classification methods for two participants can be seen in plots 6.8 and 6.9 below. It is apparent that in the original classification generated by the algorithm the separation between M (moving) and NM (non moving) clips is not clear. The findings from the two classification methods but also from the initial manual classification are presented in the section 6.4.2 below.

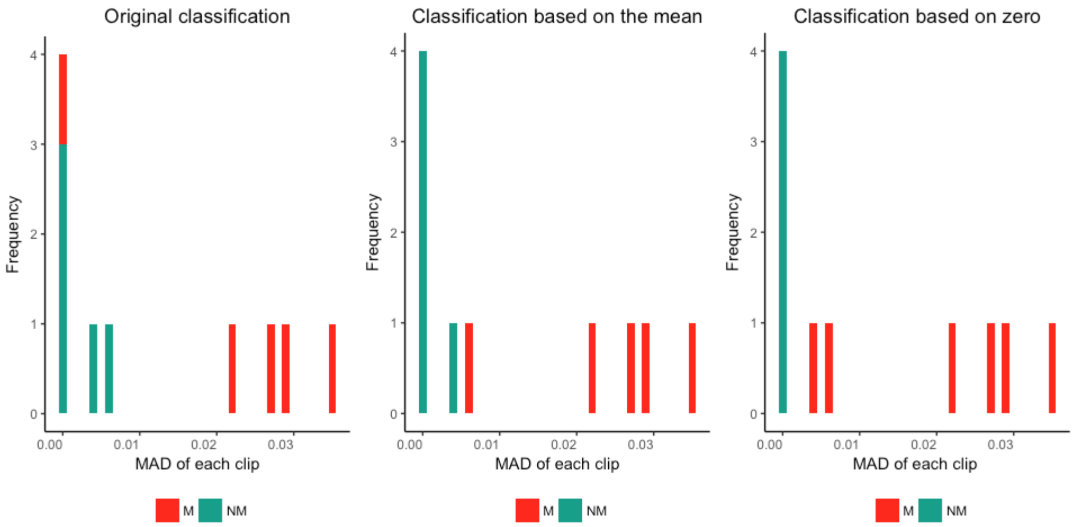


Figure 6.8: Classification histograms for participant ACCA00062. M = Moving, NM= Not moving

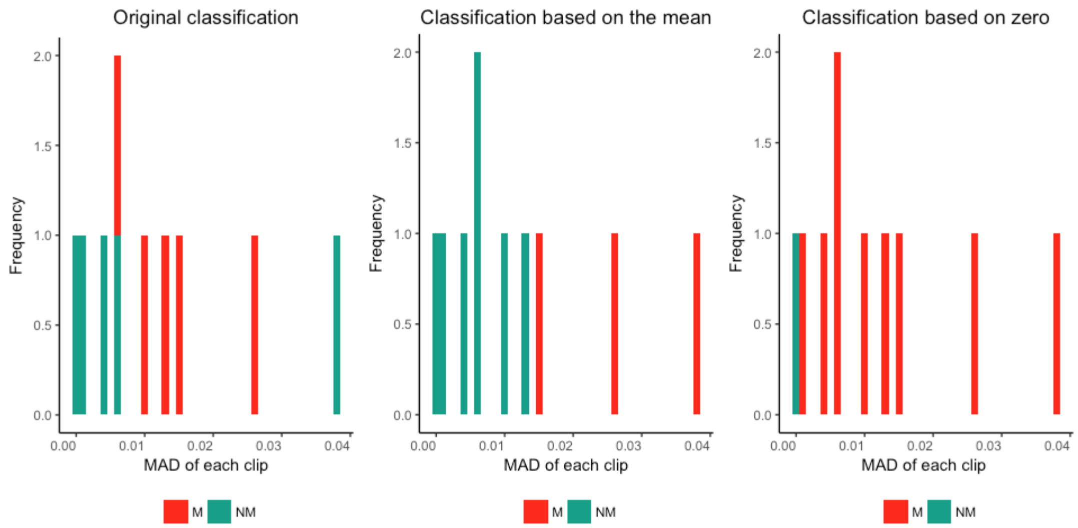


Figure 6.9: Classification histograms for participant ACCA001D6, M = Moving, NM= Not moving

The surveys were hosted in a server located within Queen Mary and were encrypted with a user name and a password that were given to each participant to access the survey. The survey was divided into 2 sections. The first section showed the 10 video clips in a random order and asked participants to indicate how well they remembered each clip. It then asked them to select how engaged they were during this part on a scale from 0-10 by moving a slider (0 = "Not at all Engaged" and 10 = "Very Engaged"). The participants were advised to watch the videos as many times as they wanted. In the second section the same 10 video clips were randomised and listed again for the participant to put them in an order of preference. A screen shot of the original form is included in Appendix C.

Surveys were sent to each participant two weeks following the day of the performance and again a week after that to correct for a mistake while selecting the clips. Only the responses from the second corrected distribution of the questionnaire, were used in the results presented above. This was 3 weeks after the day of the performance which was still considered a reasonable time for participants to remember the performance.

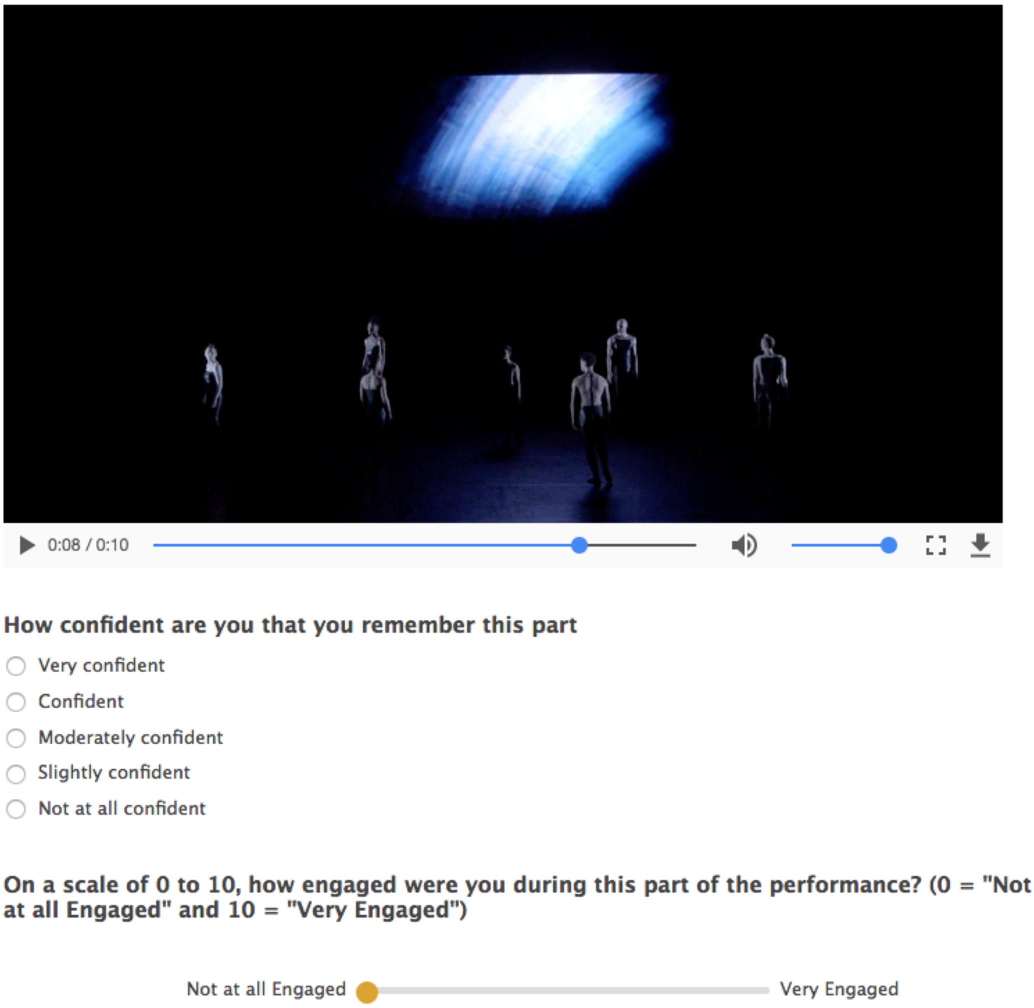


Figure 6.10: Screen shot taken from Survey II, section I showing an example of a performance clip for one of the participants

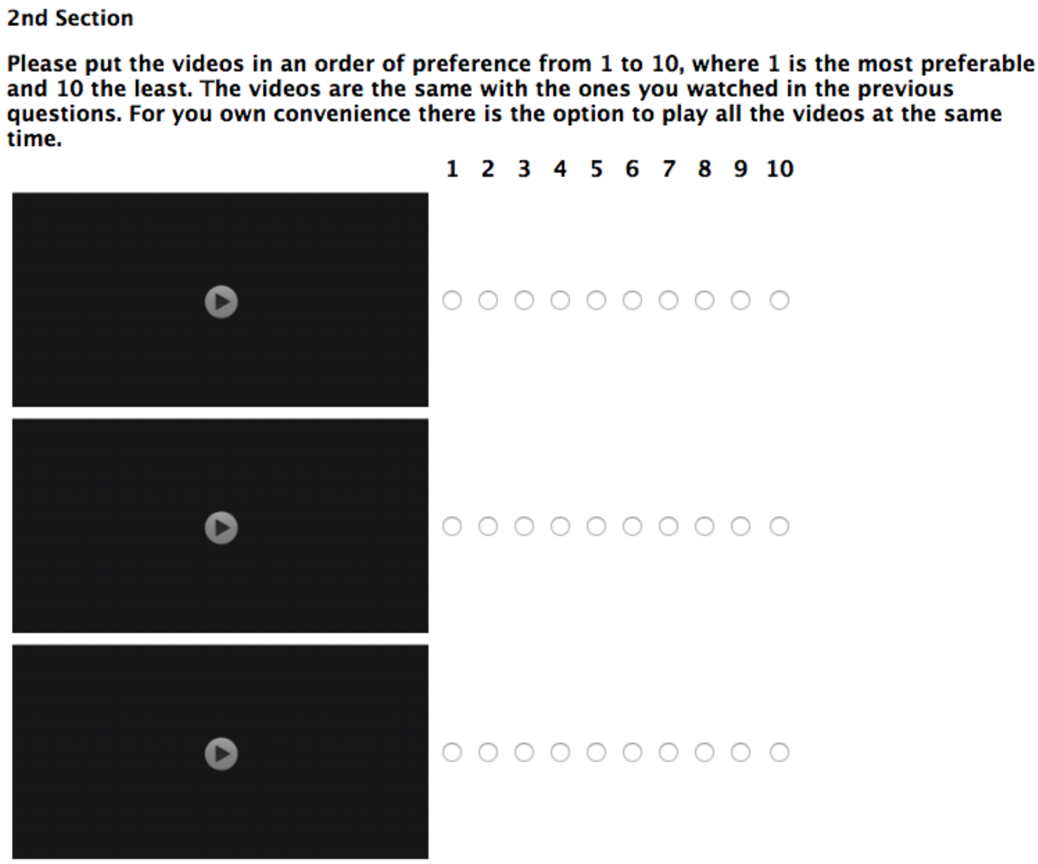


Figure 6.11: Screen shot taken from Survey II, section II showing an example of a performance clip for one of the participants

## 6.4 Results

The results are reported in three parts. Firstly, the results from Surveys I and II are presented to test the key hypothesis that less movement in the audience is associated with moments of audience engagement (H2). Secondly, any possible differences between the left and right hand behaviour are examined to test hypothesis 1 (H1). A final test was also carried out to identify relationships between the continuous metrics of audience and the elements of the performance (H3). The key findings are summarised at the end of this chapter in the reflective summary section.

### 6.4.1 Survey I: General evaluation of the piece

Figure 6.12 below shows the responses separately for each of the eight statements of the questionnaire. Each survey item is represented as an individual bar graph showing the percentage for each response category. All bar graphs are uniformly normalised to the highest occurring percentage. In summary, the survey results indicate that the majority of participants (71.4%) enjoyed watching the performance while only 7.1%

found it boring. Interestingly, two out of the three participants that did not enjoy the performance were professionally connected to dance.

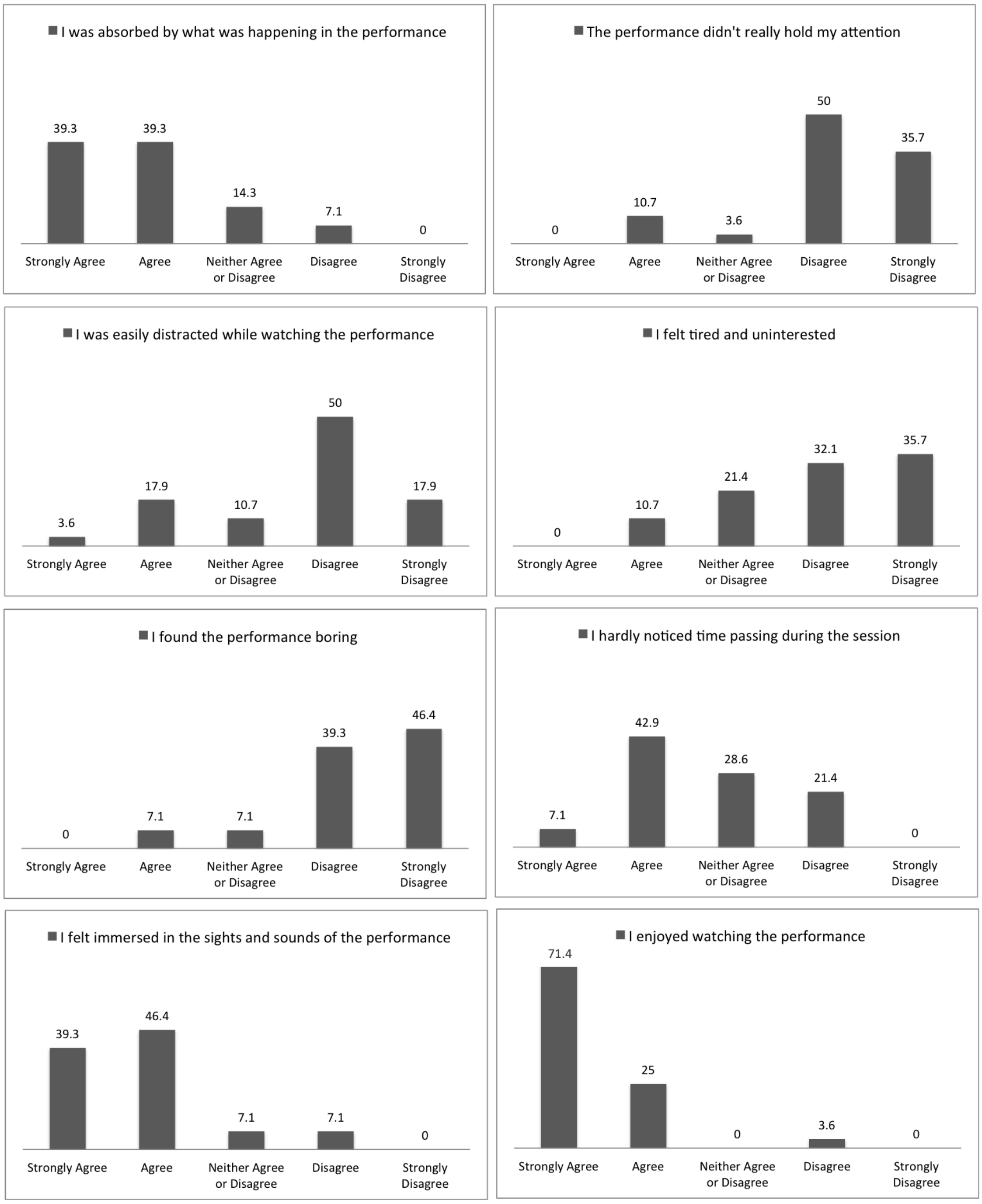


Figure 6.12: Post-performance questionnaire results (n = 28). Individual bar graphs showing the percentages for each response category

When asked about any specific moments of preference during the performance, 82.1% of participants said they did have had some favourite parts in the performance while 35.7% said they found some parts boring. In summary, the conclusion drawn from the participants' open ended answers was that participants highly agreed on their favourite parts in the performance. Interestingly most of these parts were in the beginning and at the end of the piece. Seven participants mentioned as their favourite part the final part of the performance while eight people said that their favourite part was at the very beginning of the peace. Examples of participants' descriptions of favourite parts are presented below:

Final part - Sun Part:

1. Especially the part with sun/red/yellow
2. last part
3. The part where the little orange sphere was gradually growing and the movements were bigger and bigger accordingly
4. The image of the sun zooming
5. and the sun scene
6. The last part where the sun appears woth the music increasing te tension along with the dancers was really well done
7. The sun at the end was incredible and I noticed myself being far more interested in that than the movement

First part - Fluid group movements:

1. the fluid group movements
2. The start of the performance when the dancers worked and were dancing as one unit
3. The first part
4. I liked when all dancers were on stage moving together as if in one piece
5. The initial scene where the dancers were dancing together in a very organic way was very engaging
6. the plasticity of the dancers while dancing together
7. initial part, choral dance
8. The start: very original and exciting - i had not seen these kinds of movements before

Aliens:

1. The dance method which transformed the dancers to robots
2. Enjoyed the movement in the 'fast forward' section.

3. The part with the piano Music where they moved like dolls

4. sometime towards the middle, something i would describe as the 'robot dance'

5. The part they were acting as if they were in fast forward Very well performed!

No conclusions were drawn regarding the duller parts apart from some of the participants' feedback regarding repetition in the movement and strong lights, both seen as negative elements.

### 6.4.2 Survey II: Identifying participants' engagement moments

The second survey was completed from 21 (7 males) out of 28 participants. On average, the results show that the participants' engagement ratings were skewed towards high values (M=6.3, SD=2.7) (see figure 6.13) which shows that participants liked most parts of the performance. This result agrees with the responses of the post-performance survey discussed above but it is not ideal for identifying relationships between movement and engagement given that in the clips there was insufficient variation between high and low engagement moments.

As discussed before, the clips were reclassified in high and low movement using two different methods except from the original method that was the one that initially was used to export the clips. Results are presented below for all three methods. Overall, even though for all the participants the average engagement levels were higher in the low movement clips compared to the high movement ones the results do not have enough statistical power to show this difference.

Specifically, for the first method where the manual classification of the clips was done based on their position on the timeline (original classification) the average engagement score is 6.30 for the high movement clips and 6.40 for the low movement clips. In the movement classification based on the mean the average engagement score for high movement is 6.1 and 6.47 for low movement. Finally, in the final case were the data were classified in the categories of "absolute stillness" or "movement", the average engagement score is 6.1 for movement and 7.04 for absolute stillness.

These three cases were tested in different GLMMs with a linear model (see distribution fit in appendices C). In each model the movement classification type was defined as a fixed factor, along with the order of the clips as they were presented in the survey. Participant ID was defined as a random factor.

Results are reported in the tables below. The model for the case that the classification was done for absolute stillness (MAD = 0) shows no effect of movement state (Moving vs. Non moving) on the engagement levels (Chi-sq=1.5681, p=0.21) while clip order also do not show an effect on engagement levels (Chi-sq=0.1343, p=0.71). Similar are the results for the other two classification methods. The model for the case that the classification was done based on the mean shows no effect of movement state on the engagement levels

(Chi-sq=0.6435, p=0.42) while the results are also not significant for the clip order (Chi-sq=0.1347, p= 0.71). Finally, for the third case of the original classification that is done based on the algorithm the results were similar. Movement state didn't have any effect on the engagement levels (Chi-sq=0.5987, p=0.43) while clip order also do not affect engagement levels (Chi-sq=1.0333, p=0.30).

Table 6.1: GLMM model for engagement levels (Movement classification - Zero)

| | Estimate | Std. Error | df | t value |
|---:|---:|---:|---:|---:|
| Classification - MAD=Zero (Not moving) | 0.55 | 0.44 | 205.75 | 1.25 |
| Question order | 0.02 | 0.06 | 189.83 | 0.37 |

Table 6.2: GLMM model for engagement levels (Movement classification - Mean)

| | Estimate | Std. Error | df | t value |
|---:|---:|---:|---:|---:|
| Classification - Mean (Not moving) | 0.31 | 0.39 | 199.07 | 0.80 |
| Question order | 0.02 | 0.06 | 190.39 | 0.37 |

Table 6.3: GLMM model for engagement levels (Original Movement classification)

| | Estimate | Std. Error | df | t value |
|---:|---:|---:|---:|---:|
| Original Classification (Not moving) | -0.53 | 0.69 | 189.00 | -0.77 |
| Question order | 0.12 | 0.12 | 189.00 | 1.02 |

Another interesting finding that came out from this survey was the relationship between the confidence that participants remembered each clip and the engagement score they gave to the clip. A Spearman's rank correlation shows a high correlation between the participants average confidence levels and average engagement ($p<.001$, $r=0.74$). This result shows that, perhaps unsurprisingly, the participants tended to remember better the parts that they liked the most or that they liked most the parts that they remembered.

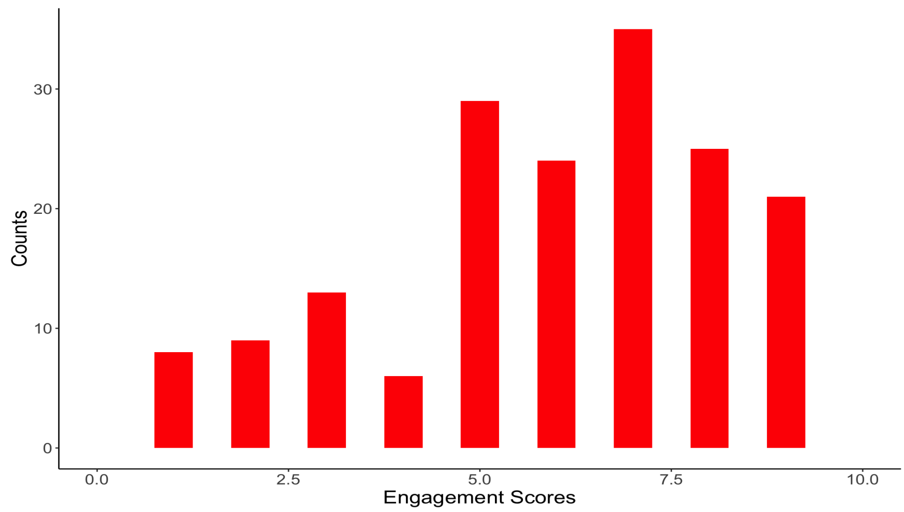


Figure 6.13: Histogram of the engagement scores of all participants

### 6.4.3 Left and right hand differences

Next the measurements were examined to identify possible differences between left and right average acceleration of the hands (H1) and also whether there is any difference in the behaviour of the dominant and the non- dominant hand. This was based on the results of studies I and II that show that audience members use their left hand more during the performance compared to the right.

The left plot in Figure 6.14 shows that the left hand moves faster during the performance compared to the right while the right plot shows that participants move their non-dominant hand slightly faster compared to the dominant. This was tested in a GLMM using a lognormal distribution. The model had two fixed factors: 1. the hand that each participant wore the wristband (right or left) and 2. whether the wristband was placed on the dominant or on the non-dominant hand. Participant ID was assigned as a random factor. As seen in the table 6.4 below, the model does not show a main effect of the hand (right or left) on the average acceleration of the hands (Chi-sq=0.04, p= 0.82) while no difference is found in the movement intensity of the dominant versus the non-dominant hand (Chi-sq=0.24, p=0.62). Regarding the interaction between hand asymmetry and handedness, the results are also not significant (Chi-sq=0.03 , p=0.85).

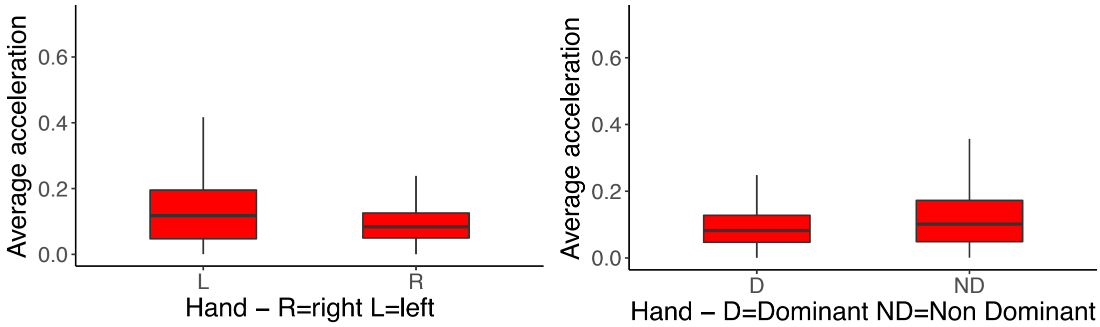


Figure 6.14: Average acceleration across all participants of the left and the right hand (left plot). Average acceleration across all participants of the dominant and the non-dominant hand (right plot)

Table 6.4: GLMM model for average acceleration (Left vs right hand)

| | Value | Std.Error | DF | t-value |
|---:|---:|---:|---:|---:|
| Sensor Hand (Right) | -0.00 | 0.01 | 26.00 | -0.22 |
| Dominant Hands (Non-Dominant) | -0.00 | 0.01 | 26.00 | -0.49 |
| Sensor.Hand (Right):Dominanthand (Non-Dominant) | -0.00 | 0.02 | 25.00 | -0.18 |

### 6.4.4 Audience - Dancers Interaction

As in studies I and II, this section describes the tests for any possible connection between audience responses and different performance elements. The first test was about the movement simulation hypothesis which supports that audience movement can be influenced by the movement of the dancers (H3). Following this, tests were also carried out to find whether other elements of the performance such as the projection or the soundrack influenced the movement of the audience.

The first plot on figure 6.16 below shows the audience magnitude of acceleration during the performance. In this case the magnitude of acceleration was used and not MAD as a metric since no averages were involved in the calculation. The three plots below show the data from the three important elements of the performance: the average velocity of the dancers, the average velocity of the projection screen and the power of the soundtrack. Overall, from the first plot it appears that there is a decrease in the movement of the audience as the performance progresses. This finding agrees with the finding of the first study and will be further discussed in the followng chapter.

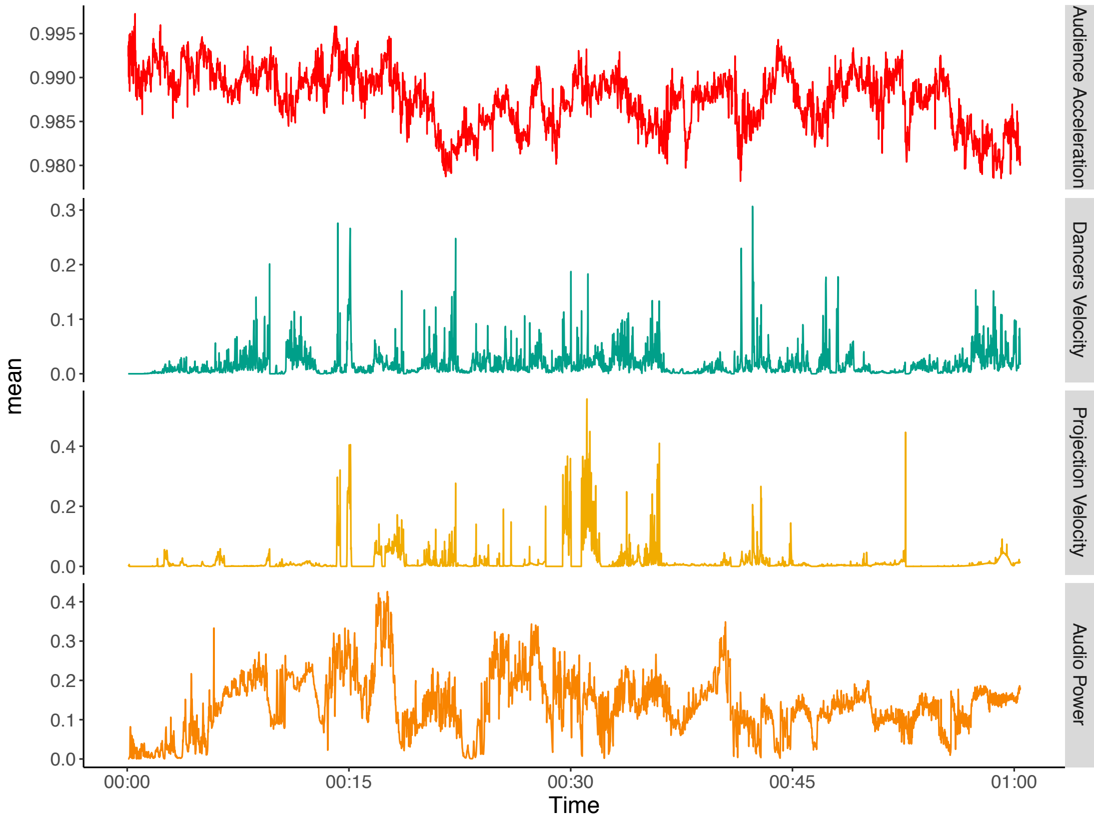


Figure 6.15: Timeseries of audience, dancers, projection and audio averaged every 1 second

Similar to Study II, Granger-Causality (GC) analysis was used to identify any possible relationships between the movement of the audience and different elements of the performance. This was examined for lags between -9 and +9 seconds. Positive lags indicate that the performance timeseries predicting audience movement while negative lags indicate the opposite (Figure 5.20). Causality was tested separately between audience magnitude of acceleration and dancers average velocity, audience magnitude of acceleration and projection average velocity and audience magnitude of acceleration and audio power. Relationships between audience-projection and audience-audio were considered predictive only if they are unidirectional. To ensure stationarity, all timeseries were differenced by subtracting consecutive sample points from each other prior to applying GC.

Overall, the GC results show that dancers movements do not systematically predict audience movement. However, the results show a systematic but unusual prediction in the opposite direction. In particular, we found that dancers movement is predicted by the movement of the audience at a 5-second lag order $F(5,3599)=2.8261$, $p=0.01$, 7-second lag order $F(7,3595)=2.2982$, $p=0.02$ and 9-order $F(9,3591)=1.9398$, $p=0.04$.

There were no statistically significant GC relationships between projection and audience movements. Finally we found that the power of the soundtrack predicts the movement of the audience at a lag order of 1sec $F(1,3607)=4.0129$, $p=0.04$.

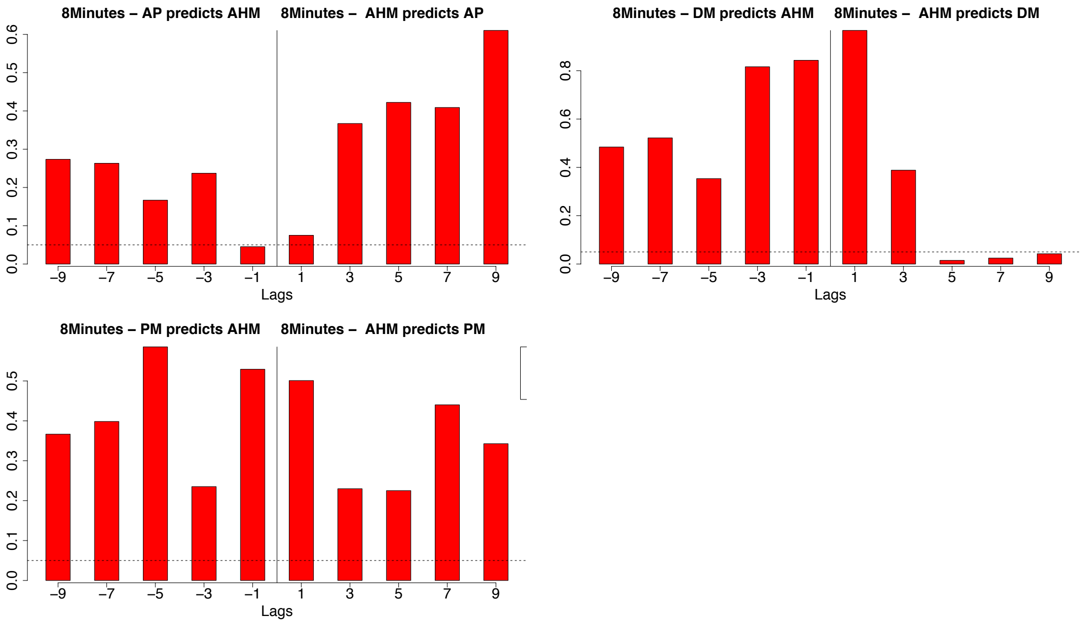


Figure 6.16: GC for audience hand movement (AHM) and audio power (AP) of the performance (topleft plot), GC for audience hand movement (AHM) and dancers movement (AM) (topright plot), GC for audience hand movement (AHM) and visual change of the projection (PM) (bottomleft plot). The x axis indicates the lag order and the y axis the p values. The dashed line indicates a significance level of $p \leq .05$

## 6.5 Reflective Summary

This chapter presents the final study of this thesis. The main aim of the study was to test whether the amount of movement and the engagement levels of the audience are inversely correlated using a more controlled methodology with recruited participants. The study also tests for any differences between the behaviour of the left and the right hand during the performance and their dependence on handedness. Finally, similar to the previous two studies, the movement simulation hypothesis is been tested and therefore whether aesthetic elements of the performance such as sound and visuals might influence the responses of the audience.

On the contrary to Studies I and II that the data was collected from a random audience sample, in this study 28 audience members were recruited to attend the performance "8 minutes" at Sadler's Wells Theatre in London. This made it possible to acquire the necessary information from the participants before and after the performance. Wearable devices were used to measure the hand movement of each participant during the performance and based on the motion data of each audience member, individual surveys were customised to measure the engagement level in response to movement.

Overall, the results of the survey do not show a clear connection between participants hand movement and levels of engagement to the performance. Even though the average engagement scores are slightly higher for the clips that participants move less there is not enough statistical power in the data to reject the null hypothesis. There are several reasons why this might be the case.

Firstly, the fact that the engagement data is skewed towards high values minimise the variation among the clips and makes it harder to identify different engagement levels. The latter, together with the small sample size of participants made the GLMM model less powerful.

A methodological limitation of this study that might have affected the result is the difference of scales between the engagement and the motion data. While the sensors continuously measured the hand acceleration of each participant (32fps), engagement levels were measured on a discrete scale. The collection of continuous self-reported engagement data might have been beneficial to better explore any correlations between the engagement and the motion data, however, it was impossible to collect such data without tethering participants with handheld devices during the live performance. One possible solution to this would be to show to participants a video recording of the same performance and ask them to continuously report their engagement levels. However, this solution violates the basic hypothesis set earlier in this thesis that it is the bidirectional relationship between audience and performers that defines the liveness of a performance.

The duration of the clips is another element that might have affected the results. Can people be continuously engaged for 10 seconds? and if they are engaged will they express this with absolute stillness? According to (Bernhardt, 2007) depending on the context, the overall body posture might remain relatively constant for periods of between 10 seconds to many minutes but at a finer scale, other subtle gestures might modulate the basic posture. The typical duration of a gesture that in our case will be a self-touching gesture might be up to several seconds. Therefore, it might be that the chosen duration of the clips was not appropriate to accurately identify moments of engagement.

A possible solution to more accurately identify moments of high and low engagement might be a more fine-grained signal processing analysis of movement. According to Witchel et al. (2014a) even though two timeseries might have similar amount of movement (resulting in similar mean speed measurements) the movement structure might be different. Their study aimed to identify moments of boredom by measuring the movement of head and shoulder of seated participants interacting with screen presented stimuli. Their results show that the range of the movement during boredom is larger, and the movements tend to be large sudden movements interspersed with long ($>$ 5 seconds) periods of stillness. On the other hand, movements during engagement are smaller and less spiky, but they are more pervasive.

Therefore, even though the results of the survey didn't provide strong evidence that movement and engagement are correlated, the results of the average acceleration timeseries show that the movement in the audience decreases as the performance progresses. This finding falls in line with the finding of the first study and brings to question whether this decrease of movement means that people become stiller as they are more focused on the performance. This influence of movement and engagement will be discussed in more detail in the overall discussion of the thesis (Chapter 7).

Regarding the live communication between audience and dancers, the granger causality (GC) analysis does not show any systematic influence of audience movement by the movement on stage as in the previous studies. Two relevant unexpected findings that came out from this analysis were that 1) the movement of the audience has a strong influence on the movement of the dancers and 2) that there is a relationship between audio power of the performance and audience movement. These results come in line with the results found in the second study and will be discussed in more detail in the next chapter.

As far as the behaviour of the left and right hand is concerned this study shows that there are no significant differences in the intensity of movement of the right and the left hand and this does not depend on the handedness of participants. This finding is not in line with the findings of the two previous studies that show that the audience members tend to use their left hand more compared to the right. One possible reason that this might happened is due to the between subjects experimental design followed in this study that made the statistical test less powerful.

Finally, an interesting finding that came out from the second survey but was out of the main scope of this thesis is the strong correlation between engagement and memory. In particular, the results of the second survey show that participants tended to better remember the moments in the performance that they were more engaged. This finding can be supported by the levels of processing theory initiated by Craik and Lockhart (1972). According to Craik and Lockhart (1972)'s theory the more you process something the better you remember it. Memories that were deeply processed led to longer lasting memories while shallow processing led to memories that decayed easily. Based on this it can be argued that participants were more confident to remember the moments of the performance that they were more engaged because they were more attentive to details during these moments. The amount of attention audiences give to the moments that they liked more might be higher compared to the ones that they didn't like and this was determined by higher depth of processing and as a result better memory. This is an interesting finding that might contribute to the definition of engagement. However it focuses on the post-performance self-reported audience responses rather than on the momentary responses that occur during the live performance and are the main focus of this thesis.

# Chapter 7

# Discussion and Implications

## 7.1 Overview

Several key findings from the preceding chapters warrant further discussion. This chapter starts with a brief overview of the findings followed by a section that describes, the contradictory responses audiences perform during the performance and non-performance parts as well as the appearance of audience overt responses and how that is expressed with signs of engagement or boredom. This is followed by the results relevant to audience-dancer interaction and their relationship with the context of kinesthetic empathy and the different aesthetic and structural elements of a dance performance. Section 7.4 proposes a new element of audience engagement supported by the findings of this thesis and makes the relevant connection with any existing literature. Finally section 7.8 proposes different uses of engagement metrics in performance and elsewhere. For the interpretation of the findings of this thesis an interdisciplinary literature is used bringing together the fields of psychology, Human Computer Interaction (HCI), performance and cultural studies.

## 7.2 Summary of Audience activities

To recap, the main aim of this thesis was to investigate the responses of a live audience during a dance performance and uncover the ones that contribute to the experience of a live performance.

The results of the three empirical studies provide enough evidence to say that audience overt responses matter. At the highest level, the most clear and obvious overt audience response is the applause at the end of the performance while during the performance social interaction and especially talking is definitely suppressed. However, a more fine-grained analysis of the data shows that audiences use their bodies and unconsciously provide signs of engagement or boredom.

In particular, the results of the studies show that audiences move very little and have predominantly expressionless faces during the performance (Study I, II) which comes in contrast to the animated facial expressions and increase of movement during the non-performance parts (breaks, interludes, applause). The findings of Study II show that compared to head and torso, the hands are the part of the body that moves significantly more. In addition, Studies I and II show that self-touching gestures (STGs) which mainly include hand-to-face gestures such as scratching, fixing hair, supporting the chin or the head are some of the activities that audiences perform. However, there are moments during the performance in which audiences stay in absolute stillness.

Regarding the movement simulation hypothesis, the results show that the movement of the dancers does not systematically influence audience physical responses during the performance while in some cases the soundtrack of the performance is what influences the audience. Unexpectedly, the results show that in a few cases a change of movement in the auditorium might come before a change in the movement on stage.

Finally, a surprising finding of this thesis is the hand asymmetry that audiences perform when watching dance. There are coherent results from the two studies that show that during the performance members of the audience use their left hand more compared to the right which is very unexpected assuming that most of the population is right handed.

## 7.3 Blank faces as an expression of concentration

During the performance the audience members were mostly seen to have blank faces while during the breaks the facial expressions were more animated, a finding that comes in contrast to the emotional hypothesis of smiling (Darwin, 1956; Ekman and Friesen, 2003) described in Chapter 2. According to the emotional expression view, a smile is a major component of a facial display associated with and caused by feelings of happiness or joy. Anything that makes a person feel good or happy should produce smiling unless the individual wants to mask or inhibit this display (Darwin, 1956; Ekman and Friesen, 2003). Based on this, one might expect audiences to express their preference on specific moments of the performance with animated facial expressions such as smiling. However, the results of this thesis show that audience members only show animated facial expressions during the non-performance parts when they are visible and are interacting with each other. This finding is consistent with the research of Harris (2017) on live stand-up comedy audiences which shows that when audiences are more visible to others and to the stand-up comedian - for example in the case that the lights in the auditorium are on - they smile and move more compared to when they are in the dark where there is no point in making visual displays for others as the display cannot be seen.

This finding comes also in line with the research from Kraut and Johnston (1979); Fernandez-Dols and Ruiz-Belda (1995) and Fridlund (1991) about social messages of smiling described in section in Chapter 2, section 2.5.2. Both studies of bowlers and

Olympic athletes show that people perform more frequent and more intense facial expressions in the presence of others compared to when alone or when there is no interaction with others. Briefly, in Kraut and Johnston's (1979) study the results show that bowlers smiled when looking at and talking to others, but not necessarily after scoring a spare or a strike. In a similar way, Fernandez-Dols and Ruiz-Belda's (1995) study on gold medallists at the Olympic games showed that medallists smiled more when they were on the podium interacting with the audience instead of when they were waiting behind the podium or when turned towards the flag during their country's anthem. A similar study was conducted by Fridlund (1991) who experimentally manipulated the presence of a friend. Fridlund (1991) reported that smiling increased with the sociality of viewing but not with reported emotion. Another study by Kraut and Johnston (1979) shows that ice-hockey fans were smiling more when they were in a social group compared to when just facing the game.

All the studies discussed above found emotional elicitors such as happiness insufficient for causing smiling, but they also found situations of social involvement make smiling much more likely. They show that people behave selectively depending on the social context and that the smiles are a social display. In the case studied here, this is supported by the fact that performances are considered as social occasions where people almost never go alone. Periods before and after the performance, breaks as well as applauses make the audience members "visible" to the rest of the audience and enable social interaction.

As opposed to a conversation where the interaction between speakers and listeners influences everyone's gestures and facial expressions (McNeill, 2008), in the case of an audience in a dance performance where this direct interaction is missing social displays are expected to be greatly reduced. Thus, facial expressions may be more representative of the cognitive-affective states that accompany the audience during the performance. In that case, the audience's blank faces are interpreted as a sign of concentration or rapt engagement connected to people's sense that they are not actively socially engaged during the performance.

## 7.4 Movement and Engagement

Apart from comparing the performance with the non-performance parts, this research also focused on the fine-grained moment-to-moment responses that occurred during different moments of a performance. The results of the second study provide evidence that there is an association of audience levels of engagement with audience body movement. The second and third studies tested this in two different surveys using short clips showing the audience (survey in Study II in section 5.4.5) and the performance (survey in Study III in section 6.4.2).

In particular, the survey in study II tested if participants were able to judge whether the audience was engaged or not during the dance performance by looking at audience clips where the audience performed high or low movement (average velocity). The results of this survey show that participants rated as more engaged the clips where the audience moved less.

On the other hand, the survey in Study III looked at a more individualistic form of engagement by looking at the hand movement of each audience member separately and their levels of engagement during the moments where the highest and lowest moments occurred. In this survey, audience members were asked to rate short clips of the performance they attended which were extracted based on each individual member's movement during the day of the performance. Even though the mean engagement scores were higher in the clips where the movement was reduced, the results do not provide enough statistical power to show a strong relationship between increase engagement and reduced movement.

In addition, the results of the first (section 4.4) and the third (section 6.4) studies indicate that the movement of the audience tended to decrease as the performance progressed. This decrease of movement can be seen both from the hand-to-face data in which the number of hands that are still on face increases during the performance but also from the audience upper-body movement that tends to decrease as the performance progresses. This finding is in line with the research by Wang et al. (2014) on audience engagement that showed that GSR readings of 10 out of the 15 audience members followed a curve where in the initial stages of the performance the readings were low and as the play progressed they increased steadily, reflecting an increase in engagement with the play across time.

This association of stillness with rapt engagement is consistent with the observations from Galton (1885) and Pasquier (2015) on engagement for audiences in lectures and theatres and with some definitions of engagement coming from HCI (Kapoor et al., 2007; D'Mello et al., 2007; Grafsgaard et al., 2012). As discussed in Chapter 2, the findings from both Galton (1885) and Pasquier (2015) suggest that audience members express engagement when in absolute stillness, while when they are fidgeting it can be assumed that the process of disengagement has already started. In a similar argument but within the context of HCI, Kapoor et al. (2007); D'Mello et al. (2007); Grafsgaard et al. (2012) suggest that diminished movement is related to engagement.

However, one might argue that the fact that the number of audience that have their hands on their faces increases as the performance progresses might also be a sign of lethargic boredom (Witchel et al., 2014b; Bull, 1978). Audiences might use their hands to support their head when they feel bored or disengaged from the performance. According to Bull (1978) a trunk posture of "leaning back" and a "supports head on one hand" posture are indicative of boredom. However, there is not a clearly articulated association between postures and their interpretation while existing literature suggests that movement which is what we mainly measure in this thesis might give us better approximations of peoples' affective state.

Therefore, in the case discussed above stillness might give the same signals to the performers for two different affective states (lethargic boredom and rapt engagement). A possible future solution for a more accurate distinction between these two cases might be a more fine-grained signal processing analysis of movement (as described in section Chapter 6, section 6.5) that focuses more on the duration of the engaging or boring moments and on the fluctuations of the signal during these periods.

## 7.5 Self-touching gestures as an expression of restlessness

In contrast to the blank faces and moments of reduced movement, the results of this thesis show that there are moments in a dance performance when audiences unconsciously move their bodies. More specifically, the body parts that audience members use the most are the hands. The results of Study II show that compared to head and torso, hands are the parts of the body that move significantly more during the performance. In addition, the hand gesture analysis in Study I shows that self-touching gestures (STGs) which mainly include hand to face gestures such as scratching, fixing hair and drinking are some of the activities that audiences perform during the performance. According to Harrigan et al. (1987) STG's appear to lack overt, intentional design and may be performed with little or no awareness. Therefore, it might be that audience members unconsciously perform these activities during the performance.

Moreover, it appears that in the survey in study II (showing audience clips to participants) the audience members may have been responding more to hand movements than head and body movement as in the survey clips the hands move significantly more than the rest of the body. This suggests that hand movements of the audience is the kind of movement that contributes more in the experience of the live performance and might be potentially detectable to the dancers.

These results also suggest that when audience members become restless, more spontaneous self-touching gestures occur. This is compatible with the literature that claims that such gestures relate more to audience boredom or nervousness (Theodorou and Healey, 2017; Mahmoud et al., 2011).

In contrast to the research presented above about stillness and engagement, the findings of this thesis suggest that increase of movement is associated with disengagement and boredom. While there is existing literature that argues that increase of body movement is associated with disengagement or boredom, there is no literature that directly connects disengagement with self-touching gestures (STGs). However, research suggests that the increase of STGs is a sign of nervousness or frustration (Butzen et al., 2005; Heaven and McBrayer, 2000). According to Ekman and Friesen (1972) STGs are gestures that people usually perform to make them feel better (Harrigan et al., 1987). Studies have shown (Butzen et al., 2005; Heaven and McBrayer, 2000) that there is an increase in STGs in stressful and fearful situations. According to Kroes (2005) bored people also tend to use their hands to support their head or perform STGs (rubbing or clutching face).

### 7.5.1 Hand asymmetry when watching dance

A surprising finding that came out of this thesis is the different behaviour of the right and the left hand. There are coherent results from the two studies that show that during the performance audiences are more likely to perform a STG with their left hand compared to the right which is very unexpected assuming that most of the population is right handed.

In particular, the results of Study I (section 4.4) show that people have their left hand up more times compared to the right hand. In addition, the findings of Study II 5.4 indicate that overall the left hand moves faster than the right. Finally, the first study indicates that the number of times people scratch their face (or head) with their left hand is slightly higher compared to the right while people use only their right hand for drinking.

However, this hand asymmetry found in studies I and II comes in contrast with the results from Lavergne and Kimura (1987) and Hampson and Kimura (1984) presented in Chapter 2 that suggest that STGs were not expected to show any asymmetry since these movements do not appear to be functionally related to either speech or a task related activity. Although in Hampson and Kimura (1984)'s study the left hand was consistently slightly preferred to perform a self- touching gesture compared to the right.

These different hand responses may indicate that people have a left-right asymmetry in their expressivity when watching dance. This is similar to the finding by Kipp and Martin (2009) about handedness mentioned in chapter 2. Kipp and Martin (2009) found that there may be a universal association of gesture handedness with the emotional dimensions of pleasure and arousal. Their study showed that handedness is closely correlated with the emotion categories in the sense that relaxed and positive emotions correlate with the use of left hand and hostile emotions with the right hand (Kipp and Martin, 2009).

However, in most of the studies related to hand asymmetry presented in Chapter 2, STGs were measured simultaneously during specific verbal or non-verbal tasks where the one hand might be occupied with a specific task. This might provoke biased results that might have affected the results of the studies.

Overall, since there is no literature relevant to hand asymmetry in performance, it is hard to sufficiently interpret this finding. However, this hand asymmetry is an interesting finding that can be useful for the design of future technologies for the audience and can be explored more carefully in the future.

## 7.6 Mimicry as a form of dynamic engagement

The systematic communication between audience and performers is one of the secondary hypotheses of this research. This hypothesis came out from the kinesthetic empathy concept described in Chapter 2. Even though, kinesthetic empathy cannot be directly tested, as the focus of this thesis is on the overt audience responses (see more information about kinesthesia in 2.4), mimicry or movement simulation are some of the concepts that were explored here. Movement simulation is considered as a form of dynamic audience engagement in dance that supports the systematic live communication between the dancers and the audience. Even though most of the studies focus on the influence that the movement of the dancers might have on the audience, this research tests for any possible influences coming from both directions - from the dancers to the audience but also from the audience to the dancers. Apart from just focusing on the movement of the audience and the dancers, this thesis also tests for any influence between audience responses and other aesthetic elements of the performance such as the soundtrack or the visuals as well as specific choreographic moments that are mentioned by the choreographer.

The overall results that came out from the three studies do not show any systematic influence in the movement of the audience by the movement of the dancers. However, some unexpected findings show that for specific lags, the movement of the dancers is influenced by the movement of the audience. In addition, in some cases the soundtrack of the performance influences audience responses.

In particular, as seen in the diagram 7.1 below, Study I does not show any influence between the overall movement of the audience and the dancers. However, as mentioned in Chapter 3 some caution is required in interpreting this result due to the inaccurate synchronisation between the videos of the audiences and dancers which occurred due to limitations of the acquisition hardware. Following that, in Study II, Part 1 does not show any influence between audience and dancers movement while the results show a bidirectional relationship between audio power and audience head/torso and hand movement. For Part 2 the GC results show that both audience head/torso and hand movement predict dancers movement while there is no influence from the volume of the audio. A similar pattern exists for Part 3 which shows that audience head/torso movement predicts dancers movement. Finally, the results for Part 4 show a bidirectional influence between audience hands and dancers movement as well as a unidirectional influence of audio power on audience hand movement. For Study III, the results show an influence of audience hand movement on dancer movements while audio power influences the hand movement of the audience.

The fact that the movements of the dancers is systematically affected from the movement in the auditorium is an unexpected finding which is not supported by any of the existing literature and is particularly strange for a contemporary dance performance which most of the times has a predefined choreographic structure. This finding could be more easily explained for a performance such as stand-up comedy or a music concert where a more direct interaction exists between the audience and the performer(s) while it is more difficult to be interpreted for a contemporary dance performance with a traditional seated audience.

One interpretation might be that the choreography is building up specific expectations which may lead to this influence. Moments of increased movement in the auditorium indicate restlessness which might mean that audience members anticipate a transition in the choreography. In order to explain this further some of the processes that choreographers follow when building a new work need to be discussed. Choreographers do not expect from their audiences to be engaged during the whole duration of the dance performance. However, they structure their dance piece in a way that audiences will experience moments of high followed by moments of medium or low engagement. This is something that happens more easily in dance genres such as classical ballet that follow a specific narrative but is something that contemporary dance choreographers might want to accomplish most of the times without using the narrative but by employing other choreographic elements. This can be a possible interpretation of why the movement of the audience might influence the movement of the dancers.

Considering that the main hypothesis of this research supports the bidirectional communication between audience and performers this finding lead us to the question - if the audience cannot influence the choreography or the movement of the dancers - how are the dancers then responding to the aggregated movement produced by the audience?

Another interpretation of the latter finding that also aims to give an answer to this question might be that the dancers - possibly unconsciously - might become more expressive when they feel a good audience while the opposite happens with a bad one (Orgs et al., 2016; Moelants et al., 2012). In addition, audience responses can be also used by the dancers to modulate timing. Moelants et al. (2012) research tested how the presence of an audience influenced performers during a music performance. Their results show that the pieces with slower tempo were performed even slower during the concert compared to the rehearsal, while the faster ones were performed slightly faster. Gesture analysis suggested a tendency for the singer to use more open, communicative postures during the concert, to change posture more often and take more time in the transitions. Overall, the movement analysis showed that the singer increased the intensity of the hand movements during the concert. Even though the case of a music performance might be different since there is a more clear and systematic interaction between the audience and the singer, it may be that also in the case of a dance performance, dancers put more effort in their movements when they sense that the audience is engaged.

Even though the granger causality (GS) results do not show any systematic influence on the movement of the audience from the movement of the dancers, in some cases audio power of the performance appeared to be a good predictor of audience movement.

According to Reason and Reynolds (2010) in several cases a positive response to the music appeared to facilitate a kinaesthetically and/or emotionally empathetic response to the dance, while negative or indifferent reactions to the music were associated with less empathetic responses. Even though the results show primarily that the audience got influenced by the music rather than the movement, in a dance performance these two become very closely entangled. Therefore this influence of the audience by the soundrack of the performance may be considered as a different form o kinaesthetic empathy that is based on the sound instead on the movement.

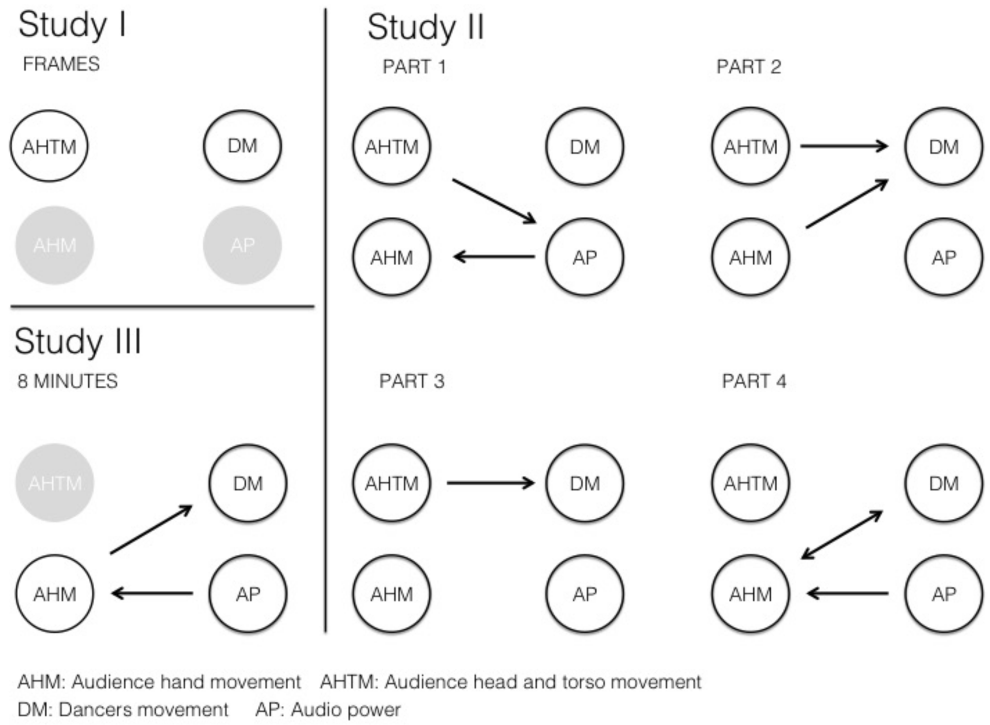


Figure 7.1: Diagram showing the relationships between audience and performance continuous responses in each of the three studies separately. The diagram is based on the granger causality (GC) results. The black arrows show the direction of the influence and whether the influence is unidirectional or bidirectional. The grey circles indicate the lack of data in Studies I and II

Finally, contrary to expectations, this study found only some marginal evidence in audience responses during the choreographic moments mentioned by the choreographer. For this, a different analytical approach is used that tested for any influence six seconds before and after the choreographic moment. This finding questions whether dramaturgic moments are the right moments to test for changes in audience responses or changes in audience engagement. It also questions the meaning of choreography in contemporary dance and suggests that the important transitions identified by choreographers might not necessarily evident to audiences. Do the audience responses correspond to the ones expected from the choreographer of the piece. Is the audience able to identify when an interlude takes place during a performance? Maybe these choreographic distinctions are likely to be more important and as a result more recognisable by expert audience members.

In terms of scale and timing, the influences discussed above came out both through the analysis of continuous responses that examined over the whole performance but also by looking on the audience responses during discrete events. GC analysis tests for any possible influences between two timeseries in different lag orders. Audience to performers and performers to audience systematic interactions were examined in the fine-grained scale of 1 second looking for possible influences in different lags from 1 to 9 seconds.

In terms of lag order, the GC results do not show a consistent pattern. In addition, for the analysis of specific choreographic moments where the effect was examined 6 seconds before and after the stimulus, the results do not warrant that 6 seconds is the ideal timing that someone needs to respond to a stimulus.

These results bring many questions on how long it takes for someone to respond to a stimulus? What time scales are likely to be relevant to investigate audience responses to the performance? Is it more reasonable to explore discrete choreographic moments or look at continuous responses? Possible answers to these questions may come through a more fine-grained analysis of continuous audience and dancers data

## 7.7 A new characteristic of audience engagement

The above discussion presented evidence from the social and cognitive sciences and from studies of live performance and suggested that a basic characteristic of audience engagement is stillness and blank faces. On the other hand, audience disengagement or boredom is supported by increase of movement and in particular with the increase of the spontaneous self-touching gestures.

However, these results can be also interpreted in the opposite direction considering that a still trunk posture of "leaning back" or a "supports head on one hand" might indicate boredom or disengagement. Similarly, on the one hand the increase of movement in an auditorium might indicate restlessness and disengagement but obvious counter-examples are easy to find: chanting at football matches, dancing at concerts, laughing at stand-up comedy. These examples can be considered as forms of dynamic engagement where audience members are actively engaged to the performance or the event using their bodies. In the case of a dance performance this dynamic engagement can be expressed through kinesthetic empathy - a concept defined in Chapter 2. The findings of this thesis show that apart from expressing engagement through stillness dance audiences might be actively engaged to the performance systematically following the soundtrack of the performance. However, this dynamic engagement is very subtle in cases like the contemporary dance where social interaction is reduced.

## 7.8 Implications: Use of engagement metrics to inform the live experience

The research presented in this thesis reveals many unknown audience responses and provides new insights about audience engagement during a live performance. This section aims to discuss some possible implications of this new realisation about audience engagement and suggests some potential uses of audience responses.

The immediate beneficiaries of this research are performance-art practitioners. Members of the audience contribute to the overall experience of the performance by sustaining it through their timely produced responses but, as already discussed many times in this thesis, not all these responses are immediately obvious. What would it mean to performing art practitioners if they could see exactly how their audiences responded during the performance? As mentioned in the section above, the goal of a choreographer is not to achieve continuous engagement throughout the performance. Choreographers plan their narrative with the goal to offer different levels of engagement to their audience. They specifically plan sections of the choreography were the audience can disengaged so that they can reengage. Choreographers build up to some expectations and find the right moment to present an engaging moment to their audience but for sure they don't want the audience to feel sleepy or bored. Therefore, the aim is to find the right balance in the piece that will include a mixture of engaging and less engaging moments.

However, moments of engagement collected by the audience itself might be different from the engagement moments that are defined by the choreographers. An example is given in Latulipe et al. (2011)'s research on audience responses to performing arts where an art practitioner attempted to interpret a lower aggregate arousal mentioned by an audience member during a segment of the dance piece when a higher arousal was expected. According to Latulipe et al. (2011) performing art experts are interested in data collected from the audience to understand and address unexpected or long periods of low arousal rather than to use the data to make second-by-second adjustments to increase arousal level. This might inform their piece and adjust it accordingly. Audience data can also be used for pieces that the art practitioners aim to restage or to make comparisons between different works and identify similarities in choreography that affect the audience in particular ways.

Finding ways to measure moment-by-moment audience engagement in real theatre settings is essential for getting a better understanding of the live experience. While live audience response metrics can be used as a way of analysing or "debugging" a performance, they can also enable new forms of responsive, creative intervention that can enhance the experience of the audience. Armed with the knowledge of what the seated audience is doing during the performance one may now enhance the experience using technology for example by feeding the continuous audience behaviour measurements as feedback that can influence the performance in real time. These ideas come to the forefront of the current discussion on interactive performances but they also raise many questions on the nature of the creative process as well as the creator's willingness to accept such unpredictable effects in their work. Real-time tracking of audience responses would add a new flavour of input to entertainment, providing dynamic forms of audience participation to the performance as well as may inform the designs of new performance spaces where the audience won't be restricted to sit quietly on a chair as in a traditional theatrical space.

Audience metrics could also be used for education and training purposes i.e. to inform tools able to train performers to perform in front of an audience. Existing research provides audience simulations to manage performance stress offering to musicians access to real-life performance scenarios (Williamon et al., 2014) as well as interactive virtual environments to train teachers (Barmaki and Hughes, 2018). The results of this thesis can be used for the development of more accurate interactive virtual audiences that will are able to simulate fine-grained audience overt responses that change depending on the performance.

Moreover, there are many commercially minded organisations that wish to understand their audiences and aim to achieve high audience engagement. There is an increasing interest from several UK research councils in "audiences of the future" and "creative industries". Their main focus is to create immersive experiences, products and services that capture public attention and enable the UK to lead. Their goal is to design new immersive technologies to improve the experience of entertainment, art, shopping and education. However these strategies focus on changes in individual consumption of services but they do not think about the important elements of the live experience discussed in this thesis such as the dynamics of audience interaction and the feedback channels to performers. Consultants and marketers claim to teach techniques and to understand social behaviours but these are rarely based on empirical studies. Without a complete understanding of how individual actions produce the interactional dynamics of an audience, attempts to design either a performance or a technology to engage that audience are at risk of failing to achieve the intended effect. We believe that the findings of this research can inform the way businesses design new technologies but may also inform the research of other audience researchers that face the same issues around sense-making of disparate measures.

## 7.9 Summary

This chapter has drawn together the results of the three studies, compared and discussed them, and presented the main findings of this thesis. The chapter started with a presentation of the activities that a dance audience performs during a performance, focusing on the most overt one that is the movement of the hands but also on the moments of stillness and blank faces of the audience.

Following this, the three main findings of this research were presented. Firstly, the broader finding of the absence of audience facial expressions during the performance as opposed to the animated ones during the breaks that social interactions occur was discussed in section 7.3. Secondly, section 7.4 investigated the inversely correlated relationship between movement and engagement based on the existing literature but also some contradictory examples were discussed. Finally, audience self-touching gestures (STGs) and increase of movement during the performance were discussed and interpreted in section 7.5 as a possible response of audience restlessness and boredom. Section 7.6, moved from the non-periodic audience responses to the more systematic audience-performer and performer-audience interactions testing the concept of kinaesthetic empathy but also any possible influences between audience responses and other aesthetic elements of the performance. Finally, based on these findings, a series of implications was proposed in 7.8. The following chapter concludes this thesis with a brief summary, and points out limitations and avenues for future work.

# Chapter 8

# Conclusion

## 8.1 Overview

This concluding chapter summarises the key findings and their input in answering the research questions of this thesis. It aims to do so by departing from the detailed examination of audience responses in order to reflect at a more general wider scale. The various methodological limitations are presented and the thesis concludes with a summary of proposals for potential avenues for future work.

## 8.2 Aims and contributions

During a live performance a unique ambience is generated between two "actors", the audience and the performers. This co-presence of audience and performers is the most important component of the live experience. This is more apparent in live performances such as stand-up comedy or during a rock music concert and is much more subtle in performances such as contemporary dance or opera where there is a clear division between the audience and the performers.

In a dance performance the dancers are on a raised stage under bright lights, while the audience sits in the dark auditorium observing the performers. In most cases, following the act, the performers can describe the impressions they have of their audience. They can distinguish between "good" and "bad" audiences or between moments of intense engagement, "crackle", "movement", "lift" , and moments of "drop" and "drift" (Healey et al., 2009). These moments define the live performance as viewed by the performers, but little is known about how, why or when they occur.

The main aim of this thesis has been to study and uncover these moments in the very restricted case of contemporary dance. Based on the hypothesis that audience and performers follow a bidirectional relationship, this research measures and analyses these overt audience responses that may provide signs of engagement or boredom. Testing the live experience from this perspective, without focusing only on the audience and their covert responses and detaching the performers from the picture, is an understudied area in academic research.

In particular, based on a comprehensive review of previous researches into the notion of engagement, this thesis tries to identify how dance audiences express their engagement or boredom during a live performance. Since there have been no published studies (apart from Katevas et al., 2015; Gardair et al., 2011; Vincs et al., 2010; Healey et al., 2009; Harris, 2017) concerning these physical audience responses that are expressed through non-verbal cues, this work makes a number of novel contributions to the field.

Firstly, the thesis identifies and reveals some of the activities that an audience performs during a dance performance, which contribute to the live experience. In addition, it provides a new representation of audience engagement that can inform empirical analysis, theories of audience response, and the design of the live experience. Finally, it demonstrates the application of a mixed-method approach for studying and collecting continuous audience data in real theatrical settings. This methodological approach can be useful to other audience researchers and can be applied to other research fields such as advertising or education.

## 8.3 Summary of the key findings

In order to collect the research components of this thesis, a series of continuous audience and dancers' sets of data were collected through three large-scale studies set in real theatrical settings around the UK. Although a comparison among the performances was out of the scope of this research, data was collected from several performances to acquire stronger evidence to support the hypotheses. The studies were conducted at The Theatre Royal in Glasgow (Study I), The Place theatre in London (Study II) and Sadler's Wells theatre in London (Study III). The main focus of the three studies was the collection of behavioural data (specifically focused on body movement and facial expressions) from both audience and dancers. In the first two studies data was collected from a random audience sample that attended the performance the day of the study while in the third study participants with a familiarity to dance were recruited and attended a specific dance performance. The total audience data collected from the three studies was from approximately 109 audience members (this number is approximate since the sample size in each study varied depending on the method).

The results of the studies managed to unpack some of the complex fine-grained responses that might provide signs of engagement but also to distinguish between two different forms of engagement - cognitive and social.

In summary, this thesis proposes that active responses such as talking, dancing, and animated facial expressions reflect the operation of a second process of social engagement which involves the active production of social displays for recognition by others. Live performances are a form of social encounter and in this context people work, to make responses that are visible to and interpretable by, others. These displays are sometimes for performers but also frequently for other audience members. The evidence for this social display process is found in the conduct of everyday social encounters and the pragmatics of performer-audience and audience-audience communication. On the finer-scale, cognitive engagement is harder to identify since is performed with much more subtle responses. Momentary cognitive engagement is performed with a still "sit up straight" body posture, while disengagement is performed either with fidgeting and increase of self-touching gestures or with a still "slumped" body posture.

## 8.4 Limitations and future directions

Conducting audience research "in the wild" is a complex task with many uncontrollable variables like the types of performance, the sizes and types of venues and different populations of audience among others. In order to achieve the depth and detail required for this level of research, this thesis had to have a narrow scope in order to focus on the signals that audiences provide unconsciously to the dancers. The following section will reflect on the methodological limitations of the research carried out in this work in achieving the research questions provided in Chapter 1 and discuss some future directions.

### 8.4.1 Measuring audiences and dancers responses "in the wild"

The first limitation occurs from the challenges that arise when collecting data from random audience samples in real theatrical settings. While this scenario provided unbiased data from audience members who chose to attend the specific performances, it made it difficult to acquire any information from the audience members before or after the performance (Study I and II). Therefore, the analysis was conducted with missing data from the participants such as information about their dominant hand, self-reported engagement data and other demographic information that could have been useful for the interpretation of the results. This was improved in the final study (Study III) which was conducted using recruited participants. This resulted in a more controlled study with pre and post performance surveys so as to be able to more accurately test specific hypotheses.

However, even though in the final study (Study III) a more controlled methodological approach with recruited participants and wearable devices was followed, due to venue restrictions, filming of the audience was not allowed. The lack of audience video recording made it difficult to interpret audience acceleration data. Video recordings would have helped to observe what people were actually doing during these moments and use these to compare with the sensor data. Sensor data can provide accurate continuous responses but when used on its own the interpretation of the data is not always accurate. In order to be able to collect good quality audience data from a big enough sample size, in such an explanatory study like the one studied here, a combination of sensor data and video recordings is needed. This was not possible in this research due to budget limitations.

Overall, more participants and a combination of sensor and video data would have increased the statistical power of the analysis and boost confidence in any findings. Future work must involve a larger sample of audiences where their responses will be measured using a combination of video recordings and sensor data. While this methodological approach may be quite expensive to undertake, it will provide more accurate results.

Another limitation of this study that has to be considered is the lack of data collected from the performers. Since the research question of this thesis focuses on the bidirectional relationship between audience and dancers, collecting continuous or post performance data from the dancers would have been beneficial. However, this was not possible due to time and technical limitations.

To be more specific, in order to gain stronger evidence of what dancers are able to detect from the auditorium, it would have been beneficial if the dancers were interviewed straight after the end of their performance or possibly given a post-performance survey to fill in.

### 8.4.2 Scientific tools to measure fine-grained audience responses

In a broader picture, another issue that appeared after conducting this research relates to the difficulties faced during the analysis of human behavioural data that have been collected from real theatrical settings. This kind of analysis is an inherently multidisciplinary problem and there is no existing method that can analyse social non-verbal interactions. There are no tools that can capture and analyse peoples' social interactions, patterns between interacting individuals or the dynamics in an audience or a crowd. Non-verbal behaviours can be ambiguous and sometimes may not be associated to a specific meaning. Their appearance can depend on factors that have nothing to do with social behaviour. For example, postures correspond in general to social attitudes, but sometimes people need to make them to feel more comfortable. Moreover, the same signal can correspond to different social behavioural interpretations depending on the context.

One way to deal with this is to use multiple behavioural cues extracted from multiple modalities so that the problem can be approached from different aspects. Improved data analysis techniques with a focus on sophisticated digital signal processing algorithms will be beneficial and provide a more accurate analysis of audience and dancers data.

In general, audience research and the area of human to human interaction would benefit from the collaboration among people from different disciplines. For example, engineers must include social sciences in their reflection, while social scientists must formulate their findings in a form useful for engineers and their work.

Overall, the present work reveals the need for new scientific tools that will be able to measure fine-grained audience responses and make sense of those measures. Audience research needs to change direction and look in more detail at what is happening. Surveys and questionnaires should be used in a more efficient way but not used as the primary source of data for analysis. Performance unfolds in time and it is not efficient nor accurate to summarise a whole performance piece based on one number or one sentence.

## 8.5 Closing remarks

It is relatively commonplace to assert that a performance, or any work of art, is only completed through the engagement and within the experience of an audience. Audience signs of engagement during a performance are really hard to be accurately measured.

This thesis aims to recognise the distinction between cognitive and social engagement processes which is critical for interpreting what audience response measures mean. For live performance, the validity and status of audience response data depends on knowing the social context; not just whether other people are present, but when and how they are interacting.

All things being equal, movement suggests boredom when watching alone but interest when interacting with others. This distinction moves us from a model of audience response as consisting primarily of individual, "internal" reactions toward a model of audience response, an "external" process, in which responses are produced and evolve as part of ongoing social interactions. This creates an opportunity to combine social science and performance in ways that can provide a new basis for the design of live experiences.

# Appendix A

# Appendix A: Study I Material

## A.1 Performance Information

**Performance title:** "Frames"

**Choreography:** Alexander Whitley

**Music:** Daniel Bjarnason

**Design concept:** Revital Cohen and Tuur Van Balen

**Lighting design:** Lee Curran

Figure A.1: Picture of the Performance "Frames" directed by Alexander Whitley

## A.2 Ethical Approval

Queen Mary
University of London

**Queen Mary, University of London**
Room W117
Queen's Building
Queen Mary University of London
Mile End Road
London E1 4NS

**Queen Mary Ethics of Research Committee**
Hazel Covill
Research Ethics Administrator
Tel: +44 (0) 20 7882 7915
Email: h.covill@qmul.ac.uk

c/o Prof. Pat Healey
CS 410 - Department of Computer Science
Queen Mary University of London
Mile End
London

2nd March 2015

To Whom It May Concern:

**Re: QMERC1432a – 1st Study: Measuring Audience Dynamics in Dance Performances.**

I can confirm that Ms Lida Theodorou has completed a Research Ethics Questionnaire with regard to the above research.

The result of which was the conclusion that her proposed work does not present any ethical concerns: is extremely low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully

Ms Hazel Covill – QMERC Administrator

## A.3 Semi-structure interview with the choreographer

**Semi-Structured interview protocol**

**Introduction**

*This is a semi-structured interview that is aimed to acquire information about the choreographic structure of the performance "Frames" made by choreographer Alexander Whitley.*

*The approximate duration of the interview will be around 1 hour and 30 minutes. The interview is divided in 2 main parts.*

**Part 1: Initial idea, basic concept**
**Duration: 30min**

*The first part of will focus on the general concept of the performance.*

1.Can you please describe the main idea behind the performance "Frames"?

2.How did you first come up with the idea?
 2.1 Is "Frames" a mixture of many different ideas?
 2.2 If yes, how did you combine these ideas in a single piece?

3.Is "Frames" an improvement or a continuation of a previous project?

4. Do you have anything else to add that is relevant to the concept of the performance?

**Part 2: Marking the video of the performance**
**Duration: 60min**

*The second part of the interview aims to the division of the performance in the most important parts.*

1.We are going to go through the video of the performance together, can you please ask me to pause the video whenever you see any important transitions or significant moments during the performance?

2.What expectations did you have from the performance during these periods of time?
 2.1 Are these expectations similar to the ones you had from the audience?
 2.2 If not, what expectations did you have from the audience during the important periods of time you mentioned before?

3.Can you please point us to any periods during the performance that something unexpected happened or something didn't work?

4. Do you have anything else to add that is relevant to this?

## A.4 Data distributions

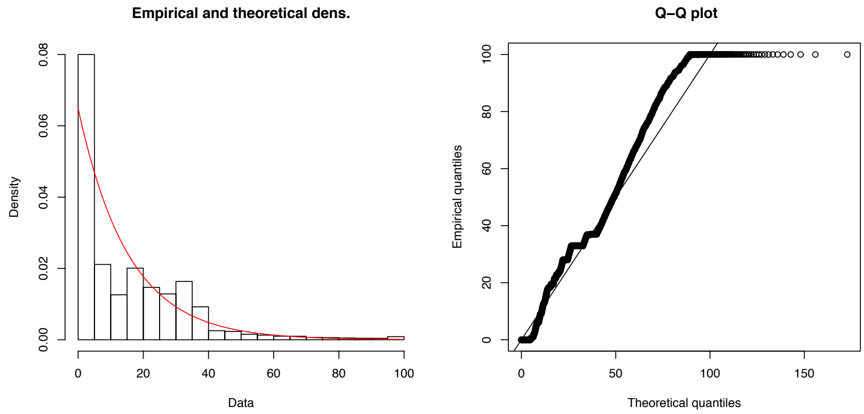


Figure A.2: Gamma distribution fit for displayed anger levels of the audience

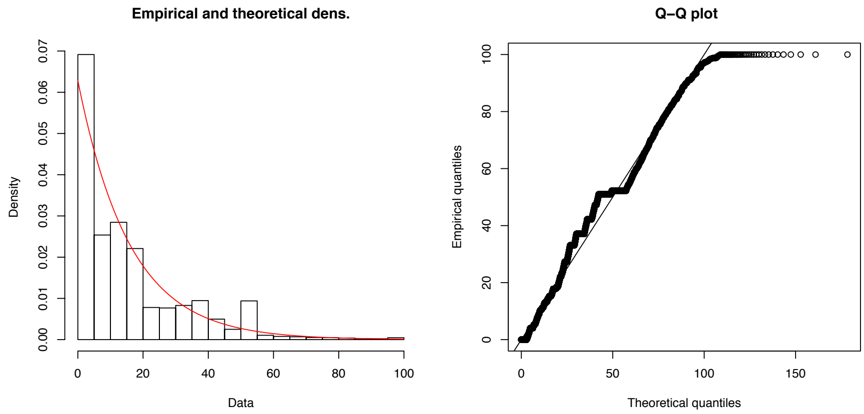


Figure A.3: Gamma distribution fit for displayed happiness levels of the audience

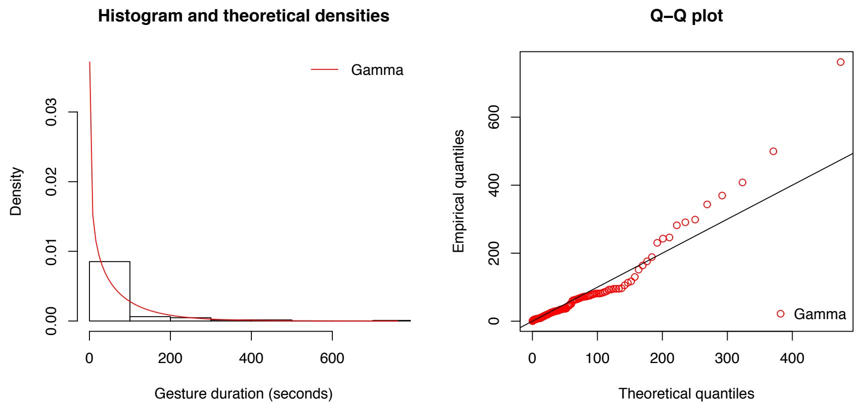


Figure A.4: Gamma distribution fit for gesture duration of the audience

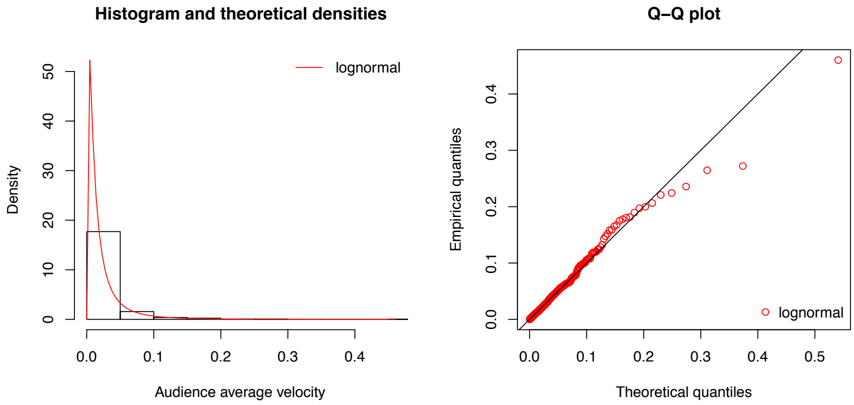


Figure A.5: Lognormal distribution fit for average velocity of the audience

# Appendix B

# Appendix B Study II Material

## B.1 Performance Information

**Part 1:** "Les femmes meurent deux fois"

**Choreography:** Danae Morfoniou

**Dancers:** Isabel Alvarez, Eriketi Andreadaki,Elena Lalucat and Sophia Sednova.

---

**Part 2:** "Triptych"

**Choreography:** Mara Vivas

**Dancers:** Julie Andreasen, Fabiola Santana and Elisabeth Schilling.

---

**Part 3:** "The Endgame"

**Choreography:** Olatz de Andres

**Dancers:** Isabel Elvarez, Elena Lalucat, Paula Serrano, Christos Xyrafakis.

---

**Part 4:** "The Tide"

**Choreography:** Tom Roden

**Dancers:**Michaela Grace Best, Bianca Brookes, Madison Capel-Bird, NamYoon Kim, King San Lo, Wai Shan Vivian Luk, Katrina Elisa Madrilejo, Ellis Saul, Kenny Shim, Rosemarie Stea, Andrew Swan, Stanley West and Alistair Wroe.

# LONDON CONTEMPORARY DANCE SCHOOL

Throughout the year London Contemporary Dance School commissions new works by a broad range of established and emerging artists. These performances give you the opportunity to watch fresh choreography whilst supporting the extraordinary artists who will shape the future of dance.

**TICKETS** £10 (£7 concessions)

**WED 3 - FRI 5 FEB** 8pm

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**THU 17 & FRI 18 MAR** 8pm

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*Wolves will be watching* by Igor and Moreno. Photo by Stephen Berkeley-White

## B.2 Ethical Approval

Queen Mary
University of London

**Queen Mary, University of London**
Room W117
Queen's Building
Queen Mary University of London
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**Queen Mary Ethics of Research Committee**
Hazel Covill
Research Ethics Administrator
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Email: h.covill@qmul.ac.uk

c/o Professor Pat Healey
CS 410 – Department of Computer Science
Queen Mary University of London
Mile End Road
London

16th March 2016

To Whom It May Concern:

**Re: QMREC1681a – Exploring Audience Behaviour During Contemporary Dance Performances.**

I can confirm that Ms Lida Theodorou has completed a Research Ethics Questionnaire with regard to the above research.

The result of which was the conclusion that her proposed work does not present any ethical concerns; is extremely low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully

Ms Hazel Covill – QMERC Administrator

Patron: Her Majesty the Queen
Incorporated by Royal Charter as Queen Mary and Westfield College, University of London

## B.3 Survey I: Ranking the performances



# Welcome to the study

We would appreciate your taking the time to complete the following survey.
The survey is about audience responses during dance performances.

Your responses are voluntary and will be confidential.

If you have any questions about the survey, please email me at l.theodorou@qmul.ac.uk.

We really appreciate your input!

*Required

1. **What is your age?**
   *Mark only one oval.*
   - 18-29 years old
   - 30-39 years old
   - 40-49 years old
   - 50-59 years old
   - over 60 years old

2. **What is your gender?**
   *Mark only one oval.*
   - Male
   - Female

3. **How often do you go and watch a dance performance?**
   *Mark only one oval.*
   - Never
   - Once a year
   - Twice a year
   - Three times a year
   - Four times a year
   - More than four times a year

4. **How are you connected to dance?**
   *Mark only one oval.*
   - I am professionally connected (e.g. choreographer, dancer etc.)
   - I like to watch dance as a spectator
   - Other: ____________

---

The question below includes links to videos of 4 dance performances. Each performance lasts for approximately 15 minutes. Your task is to watch these performances and rank them in order of preference. Please watch all 4 performances before ranking. All 4 performances include sound. For better results, make sure you watch the videos in full screen.

5. **Please put the following videos in an order of preference from 1 to 4, where 1 is the most preferable and 4 the least.** *
*Mark only one oval per row.*

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| http://www.eecs.qmul.ac.uk/~lt307/video/4thPerformance.mp4 | | | | |
| http://www.eecs.qmul.ac.uk/~lt307/video/1stPerformance.mp4 | | | | |
| http://www.eecs.qmul.ac.uk/~lt307/video/2ndPerformance.mp4 | | | | |
| http://www.eecs.qmul.ac.uk/~lt307/video/3rdPerformance.mp4 | | | | |

## B.4 Survey II: Ranking the audience



# AUDIENCE RESEARCH QUESTIONNAIRE

### Introduction

We would appreciate your taking the time to complete the following questionnaire.

Please read the following information carefully before you decide to take part.

The questionnaire is about audience behaviour during dance performances. It contains 28 questions and should take no more than 30 minutes to complete.

The information that you provide through this study will be used within my PhD research. Your participation is voluntary and your responses will be confidential. You are still free to withdraw at any time and without giving a reason.

If you have any questions about the survey, please email me at l.theodorou@qmul.ac.uk.

We really appreciate your input!

Next >>

# AUDIENCE RESEARCH QUESTIONNAIRE

## 1st Section

**Name initials (e.g for John Smith put J S)**

**What is your age?**

- 18–29 years old
- 30–39 years old
- 40–49 years old
- 50–59 years old
- over 60 years old
- Prefer not to say

**What is your gender?**

- Male
- Female
- Prefer not to say

**What is your Current Job Status?**

- Employed – Full Time
- Employed – Part time
- Unemployed
- Self employed
- Student
- Student with a Job
- Retired
- Prefer Not to Say

**Are you professionally connected to any kind of performance?**

- Yes, I am a performer (e.g dancer,actor/actress,musician etc.)
- No, I am not professionally connected to any kind of performance

**How familiar are you with the genre of contemporary dance?**

- Not at all familiar
- Slightly familiar
- Moderately familiar
- Very familiar

**How often do you go and watch a contemporary dance performance??**

- Never
- Once a year
- Twice a year
- Three times a year

# AUDIENCE RESEARCH QUESTIONNAIRE

## 2nd Section

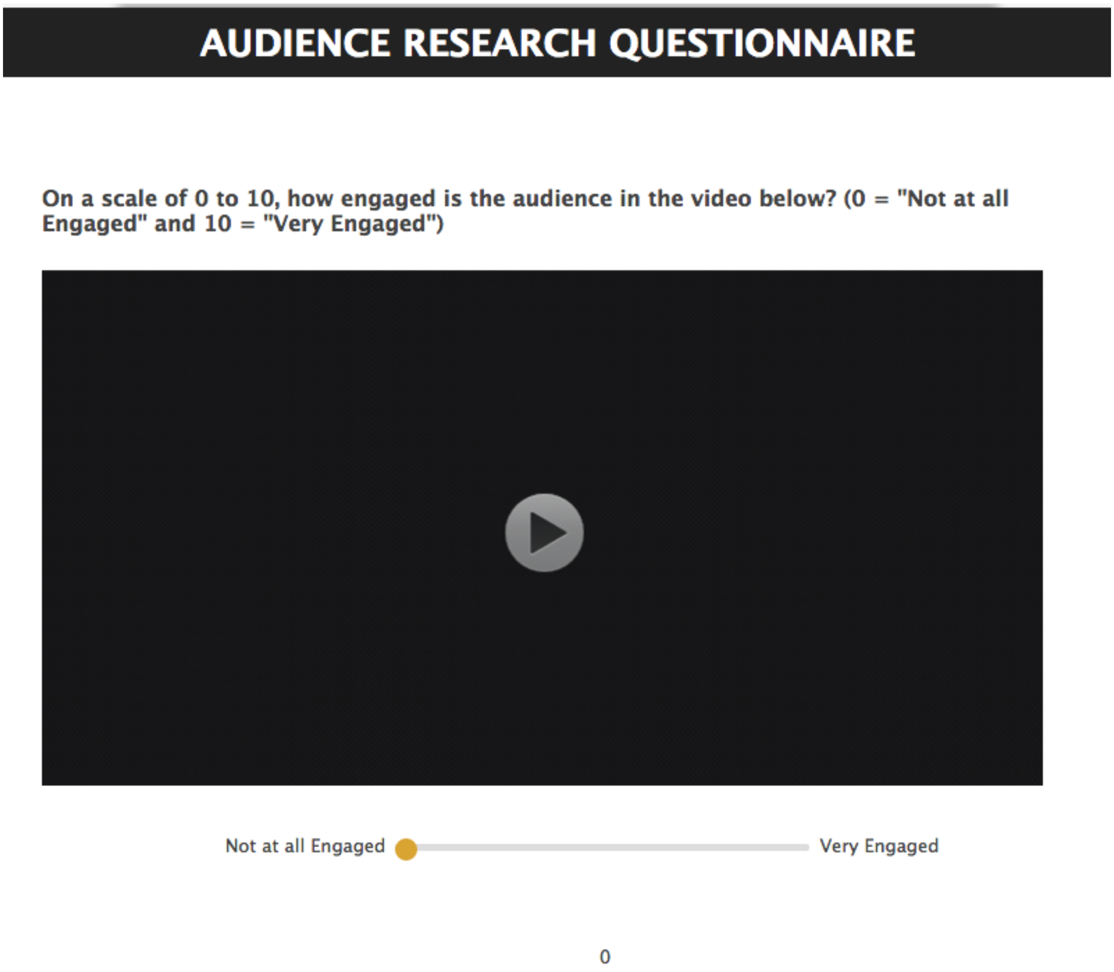
In the next section you will be shown 24 videos of an audience watching 4 different contemporary dance performances. Each video lasts from 30 seconds to 1 minute. Please ignore the fact that some audience members are wearing reflective wristbands.

Looking at the audience as a whole your task is to decide how engaged is the audience during each video. Under each video there is a slider that goes from 0 to 10. In order to move the slider, you need to select the yellow circle and then drag it where you want it.

The videos do not include sound and are placed in a random order.

You are allowed to watch the videos as many times as you want and if you change your mind about an answer you are free to go back and change it.

<< Previous Next >>




## B.5 Data Distributions

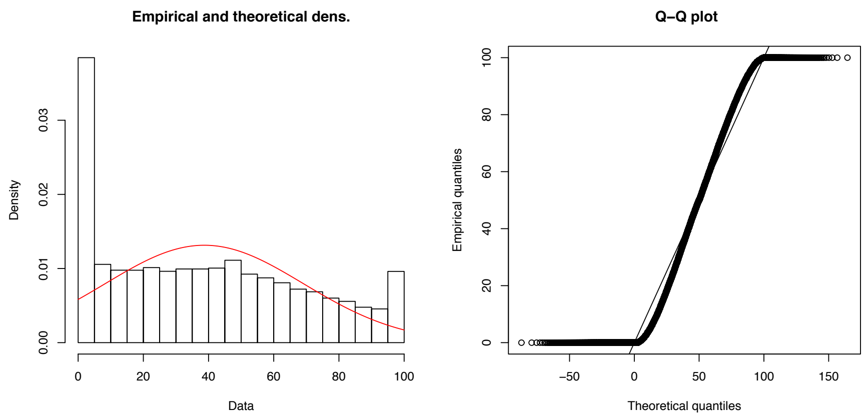



Figure B.1: Normal distribution fit for displayed anger levels of the audience

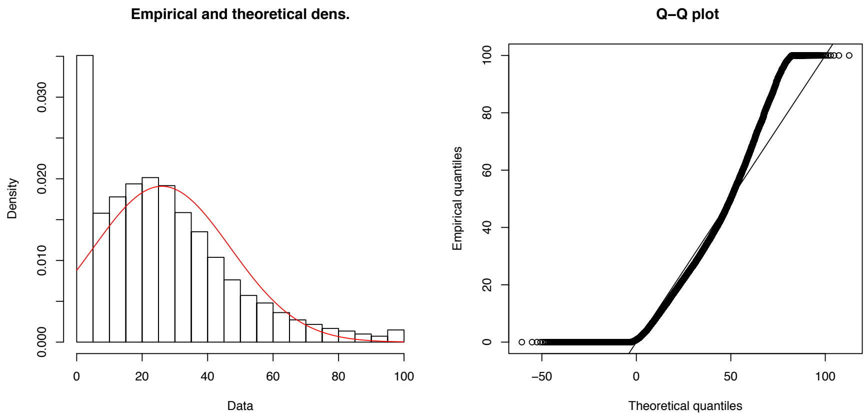



Figure B.2: Normal distribution fit for displayed happiness levels of the audience

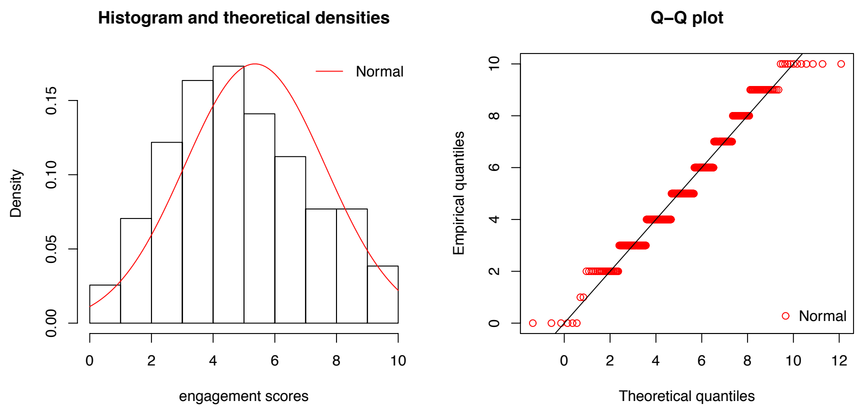



Figure B.3: Normal distribution fit for engagement scores

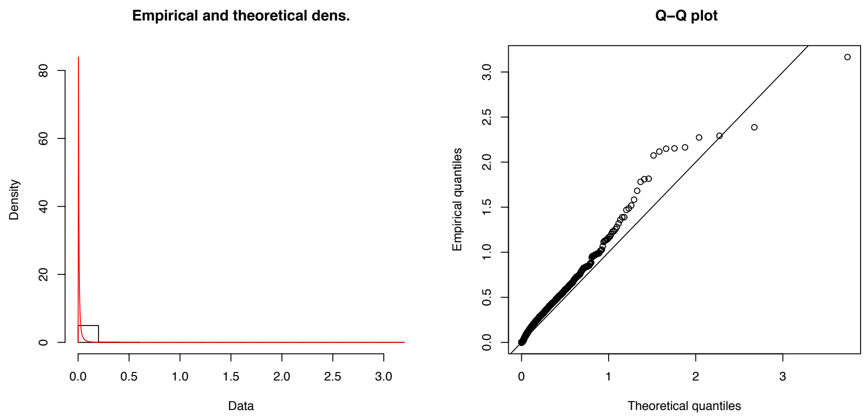



Figure B.4: Lognormal distribution fit for head, torso and hands average velocity of the audience

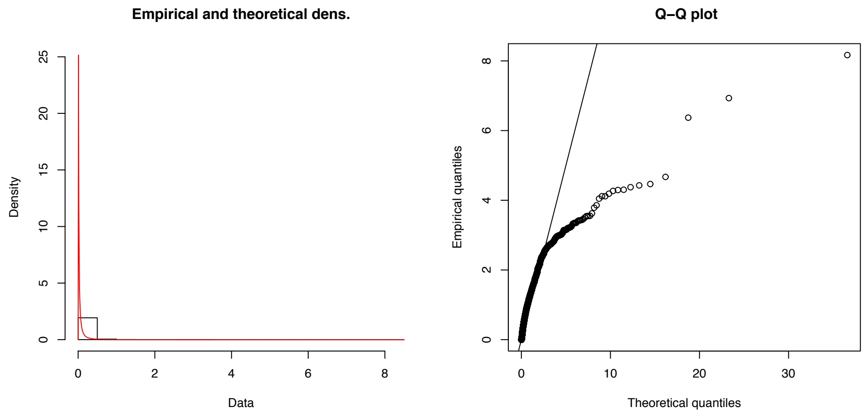



Figure B.5: Lognormal distribution fit for hands average velocity of the audience

Figures B.4 and B.5 show the distribution fits for body and hand average velocity of the audience. As seen in the plots the distributions mostly consist of zero-inflated data that occurred during the performance parts but also a few extreme values that mostly occurred during the non-performance parts but also due to sudden changes in the average velocity. This made it difficult to find a distribution that could fit well both low and high data points. However, the lognormal distribution was used in both GLMMs that gave us the best fit according to the Kolmogorv-Smirnov statistic.

# Appendix C

# Appendix C Study III Material

## C.1 Performance Information

**Choreography:** Alexander Whitley

**Composer:** Daniel Wohl

**Video artist:** Tal Rosner

**Dramaturge:** Sasha Milavic-Davies

**Costume:** Merle Hesnel

**Lighting:** Jackie Shemesh

**Lead scientist:** Hugh Mortimer

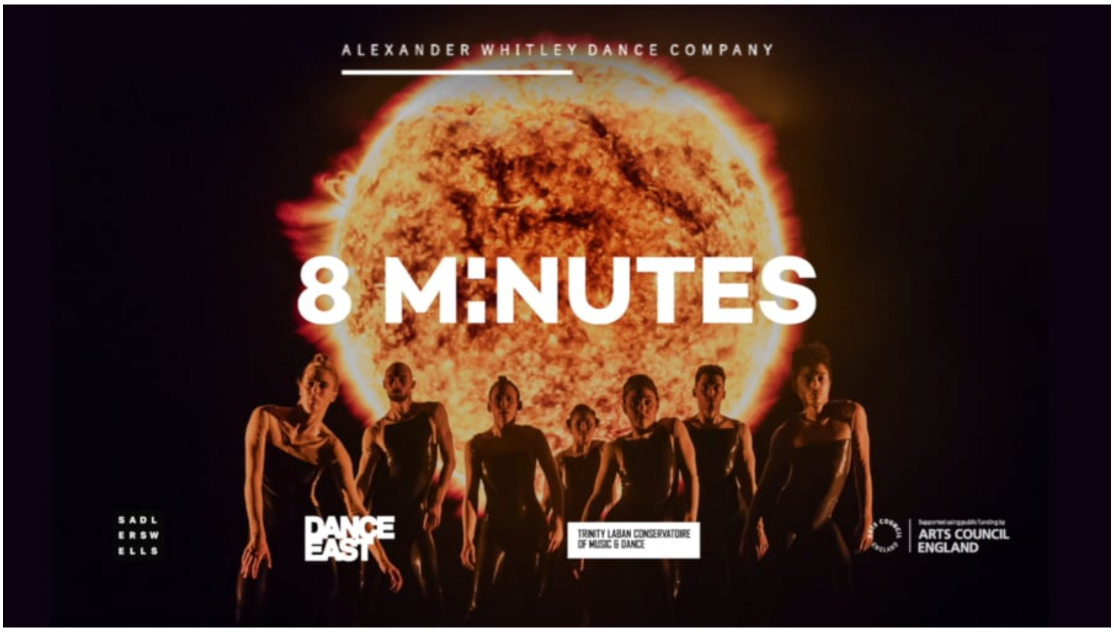



Figure C.1: Advertising pictures from the performance "8minutes" directed by Alexander Whitley

## C.2 Ethical Approval

Queen Mary
University of London

**Queen Mary, University of London**
Room W117
Queen's Building
Queen Mary University of London
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London E1 4NS

**Queen Mary Ethics of Research Committee**
Hazel Covill
Research Ethics Administrator
Tel: +44 (0) 20 7882 7915
Email: h.covill@qmul.ac.uk

c/o Prof. Pat Healey
C.S. 410
School of Electronic Engineering
and Computer Science
Mile End
London

8th June 2017

To Whom It May Concern:

**Re: QMREC1591 – Exploring Audience Behaviour during Contemporary Dance Performances**

I can confirm that Lida Theodorou has completed a Research Ethics Questionnaire with regard to the above research.

The result of which was the conclusion that his proposed work does not present any ethical concerns; is extremely low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully

Mr Jack Biddle – Research Approvals Advisor

Patron: Her Majesty the Queen
Incorporated by Royal Charter as Queen Mary and Westfield College, University of London

## C.3 Survey I: General evaluation of the piece

No1- General Evaluation of the Piece.pdf



# Survey No1: General Evaluation of the Piece

Thank you very much for participating in our study. This is the first survey you will be asked to complete.
The questions are mostly relevant to the performance you saw tonight. This survey should take less than 10 minutes to complete.

If you have any further questions please get in touch with Lida Theodorou at: l.theodorou@qmul.ac.uk

Thank you!

* Required

### Full name *

Your answer

Please indicate the degree to which you agree or disagree with the statements below by selecting the appropriate button. Please read each statement carefully before making your decision.

### I was absorbed by what was happening in the performance *

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

I felt tired and uninterested *

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

I hardly noticed time passing during the session *

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

I enjoyed watching the performance *

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

I found the performance boring *

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

Were there specific parts or elements of the performance that you liked the most? *

- Yes, I had some favourite parts
- No, I equally liked/disliked all the performance
- Not sure

If yes, can you describe your favourite parts/elements in a few words? *

Your answer

Were there specific parts of the performance that made you feel bored or elements that you disliked? *

- Yes, I found some parts boring
- No, I equally liked/disliked all the performance
- Not sure

If yes, can you describe your least favourite parts/elements in a few words? *

Your answer

Please use the space below to leave any other comments you may have about the performance or your experience during it.

Your answer

SUBMIT

Never submit passwords through Google Forms.

## C.4 Survey II: Identifying participants' engagement moments

RESEARCH QUESTIONNAIRE.pdf



# AUDIENCE RESEARCH QUESTIONNAIRE

### Introduction

Hope you enjoyed the free dance performance last week. We would appreciate your taking the time to complete this final questionnaire!

Please read the following information carefully before you decide to take part.

The questionnaire is about audience behaviour during dance performances. It contains 21 questions and should take no more than 10 minutes to complete.

The information that you provide through this study will be used within my PhD research. Your participation is voluntary and your responses will be confidential. You are still free to withdraw at any time and without giving a reason.

If you have any questions about the survey, please email me at l.theodorou@qmul.ac.uk.

We really appreciate your input!

Next >>

# AUDIENCE RESEARCH QUESTIONNAIRE

### 1st Section

In the next section you will be shown 10 short video extracts of the performance you saw at Sadler's Wells. Each video lasts for 10 seconds.

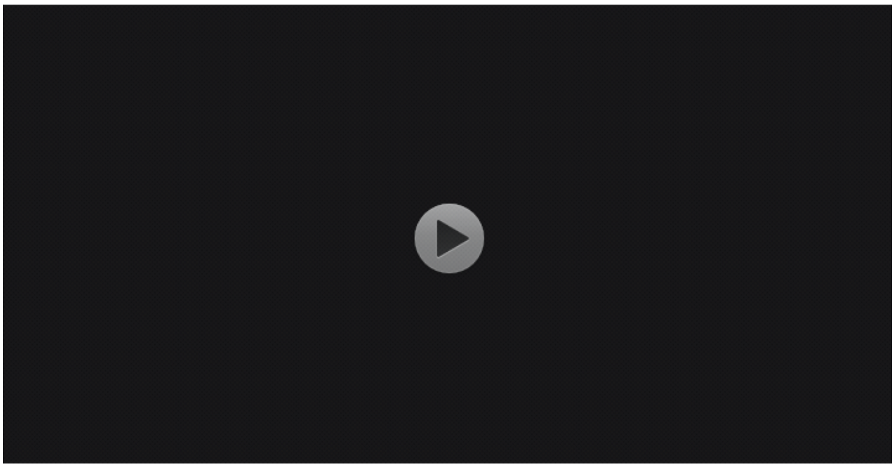
After watching each video we will ask two questions:
1. We ask you to indicate how well you remember that part and
2. Estimate how engaging you found it on a scale from 0 – 10 by moving a slider (click and drag the yellow circle on the slider)

Note: The videos include sound and are in random order.

You can watch the videos as many times as you want and if you change your mind about an answer you are free to go back and change it.

<< Previous Next >>

# AUDIENCE RESEARCH QUESTIONNAIRE



**How confident are you that you remember this part?**

- ◯ Very confident
- ◯ Confident
- ◯ Moderately confident
- ◯ Slightly confident
- ◯ Not at all confident

**On a scale of 0 to 10, how engaged were you during this part of the performance? (0 = "Not at all Engaged" and 10 = "Very Engaged")**

Not at all Engaged          Very Engaged

0

## C.5 Data Distributions

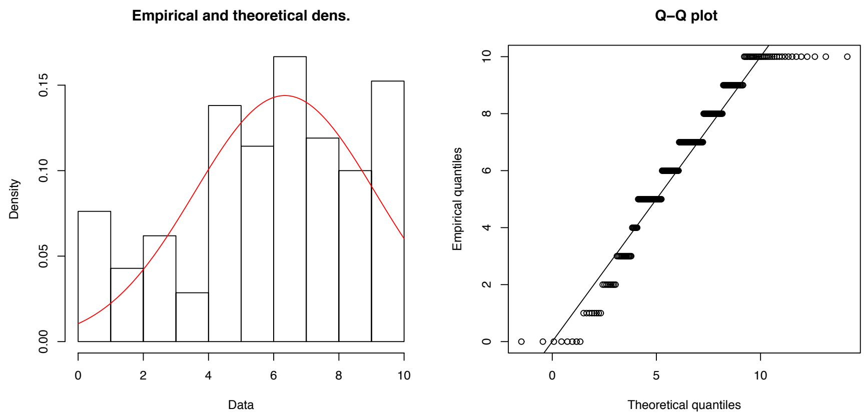



Figure C.2: Normal distribution fit for engagement scores

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